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Integrated spatial decision support system for precision agriculture

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Integrated spatial decision support system for precision agriculture

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ABSTRACT

Excessive application of plant nutrients and pesticides on agricultural land has resulted in both environmental degradation and economic loss to the farming community. Agricultural non-point source pollution was cited as the primary source of the water quality problems in many areas of the United States. Environmental concerns resulting from agricultural non-point source pollution has placed demands on farmers and ranchers to implement the best management practices (BMPs) to reduce the delivery of pollutants to streams and aquifers. Precision agriculture, a relatively recent crop production and agricultural management strategy holds great promise to minimize environmental pollution while to maximize economic productivity and profitability. It has benefited from rapidly evolving geospatial information technologies, such as global positing systems (GPS), geographic information systems (GIS), remote sensing (RS), and electronic sensors and "intelligent" controllers. However, the complexity of making routine, coherent, and cost-effective farm management decisions presents a formidable challenge to farmers. What is lacking in precision agriculture is an analytical tool that integrates these component technologies with biophysical and economic models for tactical, strategic, and policy-level decision make. In this dissertation, a decision support system called IDSSPA is developed to include modules for evaluating crop yield and chemical losses in response to site-specific management of agricultural inputs. Using this system, not only can users store, visualize, manipulate, and analyze spatial/non-spatial field experiment data, but they also can do various simulations through the easy-operated biophysical models, which take field spatial variability into account. In the system, the functionalities of the traditional models and analysis methods have been enhanced by coupling them with each other and with ArcView GIS. Uniquely desigened GIS-based interfaces enable the lumped biophysical models to incorporate and represent field spatial variability. Statistical and data mining tools are also included in the system to improve analysis of field measured data and to further enhance interpretation of model simulation results. Other components incorporated into the system are as follows: The CERES-Maize plant growth model seamlessly integrated with RZWQM to provide an alternative phonologically based model for predicting growth and yield of maize (corn), and several tools for evaluating economic and ecologic risks of precision agriculture implementation. The application examples indicated that IDSSPA is a useful research and decision make tool for precision agriculture at field and watershed scales.

CHAPTER 1
INTRODUCTION

1.1 General Introduction

Excessive application of plant nutrients and pesticides on agricultural land has resulted in both environmental degradation and economic loss to the farming community. In a 1996 National Water Quality Assessment Report to Congress, the U.S. Environmental Protection Agency (EPA) concluded that, despite significant progress made during the last several decades to control non-point pollution, significant water quality problems persist throughout the country (EPA, 1997). Using state reported water quality survey, the EPA noted that: (1) 36% of the rivers and streams surveyed, including 55% of all perennial stream miles, were partially or fully impaired with another 8% of the rivers and streams threatened; (2) 39% of surveyed lakes were partially or fully impaired with another 10% threatened; and (3) 38% of the estuaries surveyed were impaired with another 4% threatened. In addition, about 15,000 watersheds across the country were identified as either not meeting water quality standards or failing to meet expected uses (EPA, 1997). Agricultural non-point source pollution was cited as the primary source of the water quality problems in many areas of the country.

Environmental concerns resulting from agricultural non-point source pollution has placed demands on farmers and ranchers to implement management practices, such as conservation tillage, integrated pest management and nutrient management to reduce the delivery of pollutants to streams and aquifers. However, the complexity of making routine, coherent, and cost-effective farm management decisions presents a formidable challenge to farmers. Precision agriculture, a relatively recent crop production and agricultural management strategy holds great promise to minimize environmental pollution while maximizing economic productivity and profitability. The main objective of precision agriculture is to increase agricultural profit by increasing crop yield and reducing production costs, with as low negative environmental impact as possible. Precision agriculture technology can be used quite effectively to adjust agricultural inputs (e.g., lime, fertilizer, seeding, and tillage) to match agronomic requirements at different locations within the field and to account for field spatial variability.

Precision agriculture has benefited quite extensively from rapidly evolving geospatial information technologies, such as the global positing systems (GPS), geographic information systems (GIS), remote sensing (RS), and electronic sensors and “intelligent” controllers. However, what is lacking in precision agriculture is an analytical tool that integrates these component technologies with biophysical and economic models for tactical, strategic, and policy-level decision make. Because producers are fault with management decision that is tactical in nature, such tools are becoming increasingly useful on the farm (Blackmore et al, 1994).

1.2 Literature Review

While water quality has been improved over the past 25 years, the goals of the Clean Water Act (CWA) have not been met in a number of streams in that pollution control has focused on point sources of pollution through the National Pollutant Discharge Elimination System (NPDES) (Sohngen et al., 1999). Data from the United States Environmental Protection Agency or EPA (EPA, 1997) suggested that nonpoint sources are now the largest source of pollution in streams and lakes. The EPA defines the nonpoint source pollution as pollution originating from urban runoff, construction, hydrologic modification, silviculture, mining, agriculture, irrigation return flows, solid waste disposal, atmospheric deposition, stream bank erosion, and individual sewage disposal (Corbitt, 1990). Nonpoint sources take over more than 50% of the Total Maximum Daily Load (TMDL) of the nation's waters (Chen et al., 1998; Tyler, 1992; Sohngen and Yeh, 1999), and are responsible for almost two-thirds of the pollution that prevents achievement of water quality standards (Alm, 1990). Furthermore, nonpoint source pollution from agricultural and urban areas accounts for more than one-half of the biological oxygen demand (BOD) and most of the suspended solids, phosphorus, nitrogen, and toxic substances entering waterways. Thus, appropriate agricultural management practices may significantly influence water quality and environment.

Blackmore et al. (1994) reviewed the three technology levels possibly adopted by precision farming management practices, which may increase efficiency and reduce the impacts of the agrochemical wastage on environment (Logan et al., 1990; Copeland, 2000; Marshall and Bennett, 1998). Technology level one represents conventional practice with no information technology (IT) and is taken as a reference. Technology level two has some IT investment and provides farmers with an increased understanding of the enterprise, but does not include the ability to vary application rates automatically. Farmers can however achieve patch application variation by manually influencing machinery settings. This technology level is seen as an interim to technology level three which will fully support variable application rate capability.

The technology level one is the management strategy that has been built up over generations based on craft experience. It has been associated with environmental problems in four areas, including deleterious effects on the farmland ecosystem itself, pollution of watercourses and underground aquifers, direct effects on human health, and reduction or changes in desirable nonfarmed habitats (i.e. woodlands and heaths within rural areas). By financial implications, the technologies at this level could be considered as losing money through wastage, particularly of agrochemicals (i.e. nitrates, pesticides and phosphates).

In contrast with the technology level one, a farm operation at the technology level two would use an on-farm computer and software capable of supporting stock keeping, historical records and models to help predict different scenarios. Farmers using the technologies at this level would have a better understanding of the farming enterprise both in terms of day to day management needs and in on-going financial performance. The significant improvements the technologies at this level may include: (1) the use of management information and control systems that acquire data and use information to reduce risk; (2) the high efficiency of decision making; (3) assistance with the implementation and evaluation of improved business management strategies; and (4) confidence to treat on a patch basis. The technologies at this level would produce some agronomic and environmental benefits to increase yield using the same inputs or to maintain yield while using reduced inputs.

Many researches and practices at the technology level two have been conducted. Sander et al. (1994) suggested using nitrogen test for optimum management. They briefly reviewed the currently available systems for nitrogen testing, soil testing and plant analysis, and analyzed the potentials and difficulties to make a nitrogen fertilizer recommendation in terms of the testing results. How to select the model relating crop yield with applied nitrogen; how to decide current available soil nitrogen; how to define the nitrogen credits from other sources including previous legumes, rainfall and irrigation water, and manure; and how to estimate the nitrogen fertilizer efficiency may significantly influence the accuracy of nitrogen recommendations. Using field measured data, Selles and James (1999) analyzed the potentials of splitting N applications and topdressing nitrogen to maximize return. They conclude that N applied early in the life cycle of the crop improves plant growth and grain yield whereas nitrogen applied at later growth stages tends to increase protein more than grain yield, and that topdressing could be an effective tool to manage crop yield and protein. Using rainfall simulation data, Baker and Laflen (1983) studied the environmental implications of conservation tillage. They quantitatively estimated the annual nutrient (i.e. NH_4-N, NO_3-N, PO_4-P, available-P), pesticide, herbicide, and soil losses as affected by tillage for corn following soybean on soils with different erosion potentials. They concluded that the reduced soil erosion possible with conservation tillage compared with mold-board plow or clean tillage systems is an obvious advantage because of the reduction in sediment and sediment-associated chemical losses. Among some of all, the researchers who studied the effects of tillage systems on water quality include Baker et al. (1978, 1979, 1982, 1983), Barisas et al. (1978), Johnson et al. (1979), Laflen et al. (1981), Martin et al. (1978), McDowell et al. (1980), Morrison et al. (1981), Mickelson et al. (1983), and Moldenhauer et al. (1983). Based on the previous research studies on water quality protecting and improving, Baker and Johnson (1993) reviewed the current best management practices (BMPs). Randall and Schmitt (1997) assembled nitrogen BMPs in south-central Minnesota. Chester and Schperow (1985) and Logan (1990) discussed the impacts of agricultural BMPs on controlling nonpoint source pollution. Weston and Seelig (1994) introduced the experiences of using BMPs to prevent groundwater contamination in North Dakota. Recently, more researches on BMPs are being widely conducted to reduce TMDL (Chen et al., 1999).

Paralleling to the researches dominated by field experiment, researchers developed abundant mathematic models to evaluate nonpoint source pollution from diffuse agricultural areas. Crawford and Donigian (1973) developed the Pesticide Runoff Transport model (PRT) to estimate runoff, erosion, and pesticide losses from field-sized areas. Donigian and Crawford (1976) incorporated a plant nutrient component with the basic PRT model to develop the Agricultural Runoff Model (ARM) used for field-sized areas. Frere et al. (1975) developed an Agricultural Chemical Transport Model (ACTMO) to estimate runoff, sediment yield, and plant nutrients from field- and basin-sized areas. Bruce et al. (1975) developed the event model Water and Sediment Chemical Transport (WASCH) to estimate runoff, erosion, and pesticide losses from field-sized areas for single runoff-producing storms. Beasley et al. (1977) developed the Areal, Nonpoint Source Watershed Environmental Response Simulation (ANSWERS) model to estimate runoff, erosion, and sediment from basin-sized areas. Knisel (1980) developed Chemicals, Runoff, and Erosion from Agricultural Management Systems (CREAMS), a field-scale model, to estimate runoff, erosion and sediment, and chemical losses with minimal parameters and calibration. The modified CREAMS was developed to better represent the hydrology of flat, sandy, high-water-table watersheds (Heatwole et al., 1987). The models currently available for simulating pesticide fate and transport in soils range from screening models such as PESTAN (Enfield et al., 1982) to detailed research models such as LEACHM (Wagenet and Hutson, 1986). Groundwater Loading Effects of Agricultural Management Systems (GLEAMS) and Pesticide Root Zone Model (PRZM) are continuous, field-scale hydrology and chemical transport models that operate on a daily time step (Zacharias and Heatwole, 1994). The GLEAMS and PRZM models simulate chemical transport in runoff, erosion, with percolating water. It also considers foliar washoff, equilibrium adsorption, and first-order decay in foliage and soil. PRZM uses the advection-dispersion equation to simulate chemical transport in soil, whereas GLEAMS considers only the advection transport of chemicals (Kervevan and Mouvel, 1998). Both GLEAMS and PRZM use the non-uniform mixing model to simulate the transfer of herbicide to surface runoff (Heathman et al., 1986). RZWQM Team (1992) developed the Root Zone Water Quality Model (RZWQM) for modeling the interactions among hydrology, agricultural management, crop growth, and chemical fate. RZWQM uses two submodels, two-site equilibrium-kinetic sorption model (E-K) and instantaneous equilibrium sorption model (E-I), for pesticide sorption simulations (Ma et al., 1996). In addition, mathematical models simulating crop growth and yield processes were developed to model carbon balance, water balance, and energy balance in a complex crop production system (de Wit, 1965; de Wit et al., 1978; Duncan et al., 1967; Keulen, 1975). The crop models, represented by the CROPGRO CERES family, have been widely tested and used to study crop yield response to the agricultural management practices (Piper et al., 1998; Kiniry et al., 1989; Boote et al., 1988; Wilkerson et al., 1985). Jame (1996) and Matthews (1997) employed the crop models to support decision make by mainly maximizing crop yield. RZWQM Team (1999) is coupling the CROPGRO CERES family of crop growth models with RZWQM to improve the model to simulate long-term crop rotations and management practices for multiple seasons.

At the technology level three, farmers will have a full understanding of the whole process and rational decision making following the management philosophy. The trend is towards a better understanding and a smaller unit of treatment. Trying to consider spatial variability to further refine decision make, the technologies at this level will use on-farm as well as off-farm information sources. At this technology level, data collection needs to be automated, and modeling and decision support software is necessary to assist farmers making strategic and tactical decisions (Andreason, 1994; Jame and Cutford, 1996). The advanced and more accurate data collection techniques, including grid sampling, remote sensing (RS), and global positioning system (GPS) will provide huge spatial and nonspatial data (McCauley et al., 1999; Shih, 1988; Dungan, 1998). Geographic information system (GIS) has been widely used to effectively store, manipulate, and analyze these massive data to support decision make. In order to improve the performances of the existing hydrologic and water quality models, Flagg et al. (1990) and Tim (1996) suggested to couple GIS with these models. Walker (1994) used statistical techniques for assessing water quality influenced by BMPs. He employed the traditional multiple regression model to quantify the effects of BMPs. Olesen et al. (1997) developed an integrated decision support system for management of winter wheat. This system provided optimization algorithms for deciding sowing time, seed rate, nitrogen fertilization, weed control, and disease and pest control. Pedersen et al. (1997) developed an integrated farm management system. This system has been widely used by Danish farmers for economic and production management of farms. Knight et al. (1994) developed a decision support system for crop protection. Plauborg et al. (1996) developed a decision support system for irrigation scheduling. And Smith and Gledding (1996) developed a decision support system for optimizing nitrogen use in crop rotations. However, these decision support systems have several limitations of: (1) not considering field spatial variability; (2) not fully integrating the technological elements of precision agriculture, i.e., geographic information system (GIS), global positioning system (GPS), remote sensing (RS), and variable rate application techniques (VRA) (Blackmore, 1994); (3) not including biophysical and economic models; (4) not using advanced multivariate spatial statistics and high-dimensional visualization tools for data interpretation. A tool is needed to support farmers and their crop consultants when making decisions concerning appropriate treatments and levels of treatment to be spatially applied (Blackmore et al., 1994).

1.3 Objectives

As stated above, what is lacking in precision agriculture is an analytical tool for tactical, strategic, and policy-level decision make. Therefore, the specific objectives of this research are:

1. to develop an integrated spatial decision support system to facilitate data management and enhance implementation of precision agriculture at the whole-farm level.
2. to design actual example applications to demonstrate the system functions.
3. to improve the available biophysical models, the root zone water quality model (RZWQM) and CERES-Maize, by coupling them with each other and with ArcView GIS.
4. to explore potential impetus of statistical and data-mining techniques to both field experiment data and biophysical model simulation results.
5. to provide an easily usable problem-solving environment for researchers and decision makers of water quality and precision agriculture.

1.4 Dissertation Organization

This dissertation consists of abstract, seven chapters, and acknowledgements. Chapter 1, this chapter, introduces the studies and main findings in general, reviews literatures, and sets up study objectives. Chapter 2 through Chapter 5 are four papers written in a format suitable for publication in referred journals. Chapter 2, titled "Problem-Solving Environment For Evaluating Environmental And Agronomic Implications Of Precision Agriculture", describes the general structure of the problem-solving environment and gives example applications to demonstrate the system functions. Chapter 3, titled "Evaluating Environmental And Agronomic Implications Of Field Spatial Variability And Variable-Rate Nitrogen Rates", discusses how to use the GIS-based RZWQM model to simulate the benefits of variable-rate N management in maximizing crop yield and simultaneously reducing potential nitrate-N leaching losses and how to use advanced statistical techniques to interpret the simulation results. Using field measured data, Chapter 4, titled "Exploring The Implications Of Soil NO_3-N", employs multivariate statistical models to explore the effects of and interactions among the factors influencing nitrate-N leaching losses. Chapter 5, titled "Decision Tools For Evaluating Economic/Ecologic Risks Of Precision Agriculture", presents the tools used to assist decision makers to evaluate economic and ecologic benefits of the selected site-specific management practices. Chapter 6 is the user's manual of the integrated spatial decision support system (IDSSPA). And Chapter 7 summarizes the main results and findings of this study and identifies the future research direction.

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CHAPTER 2
PROBLEM-SOLVING ENVIRONMENT FOR EVALUATING ENVIRONMENTAL AND AGRONOMIC IMPLICATIONS OF PRECISION AGRICULTURE

A paper to be submitted to the Journal of the AWRA

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ABSTRACT: Precision agriculture benefits from rapidly evolving geospatial information technologies, including global positioning system, geographic information system, yield monitors, remote sensing, and electronic sensors and controllers for variable rate application technology. The potential benefits of precision agriculture include: determination of spatially referenced data for improved understanding of agricultural systems; the precise placement of agricultural inputs to improve net economic return, environmental quality, and global competitiveness; and the accurate documentation of crop production, inputs, and outputs such as grain yield. However, the adoption and implementation of precision agriculture practices demand tools for analysis of large volumes of data. Spatially explicit simulation modeling environments are essential for realistically addressing many resource management and environmental impact scenarios associated with precision agriculture. They provide the framework for evaluating the interactions between the biophysical, socioeconomic, and cultural factors in crop production and an environment for rational decision make. This paper describes the components and application of a spatially explicit problem-solving environment that can be used to evaluate the interrelated effects of precision agriculture management practices on water quality, crop yields, and economic returns. The prototype environment integrates the Root Zone Water Quality Model (RZWQM), S-Plus statistical analysis

software, and ArcView geographic information system (GIS) to examine effects of site-specific crop production practices on crop yields and environmental losses of nutrients and pesticides. The utility of the environment is demonstrated by showing how it can be used to characterize the spatial-temporal variability of corn yields and nitrate leaching losses in a 25-ha farm located near Ames, Iowa, and how to determine a reasonable simulation resolution for GIS-based crop model using a 32-acre field located near Greene, Iowa.

KEY TERMS: precision agriculture, water quality, modeling, decision support system, spatial statistics

INTRODUCTION

Research and development in agronomy has over the past decade aimed at developing less intensive and integrated farming systems with less use of machinery and lower inputs of fertilizers and pesticides (Olesen et al., 1997). Such ideas and practices can be categorized as precision agriculture. The main objective of precision agriculture is to increase agricultural profit by increasing crop yield and reducing production costs, with as low negative environmental impact as possible. Precision agriculture technology can be used quite effectively to adjust agricultural inputs (e.g., lime, fertilizer, seeding, and tillage) to match agronomic requirements at different locations within the field and to account for field spatial variability.

Precision agriculture has benefited quite extensively from rapidly evolving geospatial information technologies, such as the global positing systems (GPS), geographic information systems (GIS), remote sensing (RS), and electronic sensors and "intelligent" controllers. Using the GPS technology, soil samples can be taken across a field and their locations recorded at desired accuracy and precision. Intelligent controllers and sensors allow the producer to vary the rate of inputs according to agronomic needs to enhance productivity. GIS allows the integration, analysis, and display of all types of precision agriculture information (including data on crop yield, nutrient and pesticide application, and soil type). However, what is lacking in precision agriculture is an analytical tool that integrates these component technologies with biophysical and economic models for tactical, strategic, and policy-level decision make. Because producers are fault with management decision that is tactical in nature, such tools are becoming increasingly useful on the farm (Bouma, 1998).

This paper presents the development and application of an integrated spatial decision support system that facilitates data management and enhances implementation of precision agriculture at the whole-farm level. The decision support system incorporates the managerial, agronomic, climatic, environmental, and landscape factors that influence crop production and integrates biophysical modeling, multivariate statistical analysis, ArcView GIS to improve characterization of the agronomic and environmental implications of precision agriculture and to enhance management decision-making. The following sections describe the components of the decision support system, and are followed by an example application that incorporate site-specific production decisions in a 25-ha farmer-operated field in Central Iowa.

METHODOLOGY

The complexity of making routine, coherent, and cost-effective farm management decisions presents a formidable challenge to the adoption and implementation of precision agriculture. In crop production, for example, these decisions must be technically defensible, environmentally sound, and routinely acceptable. Effective crop management decision making also requires an underlying knowledge of the agroecosystem structure and functioning, the accumulation of quantitative information for modeling, the selection of appropriate management options that meet environmental and economic constraints, and the accurate interpretation of the model results.

Over the past several decades, computer-based environmental and socioeconomic modeling systems have been utilized to alleviate some of the bottlenecks associated with crop production decision-making. Interactive computer-based decision support systems that enable decision makers utilize data and models to resolve ill-posed and complex crop production decisions have been developed. During the past decade, these systems have evolved to encompass interactive and integrated multi-component systems that include various combinations of biophysical and economic simulation modeling, statistical techniques, heuristics and knowledge-based systems, geographic information systems, and graphical user interface components. The seamless integration of these components within a decision support framework greatly enhances the solution of semi-structured and unstructured production management problems, and is essential for addressing the multitude of agronomic and environmental impact scenarios related to implementation of precision agriculture.

Figure 1 shows the overall structure of the integrated decision support system for precision agriculture or IDSS-PA. Developed within an integrated systems research on precision agriculture, IDSS-PA incorporates various interactions and interrelationships among various elements of crop production. Its modular design enhances model construction and the manipulation, analysis, display, and visualization of large volumes of data on crop

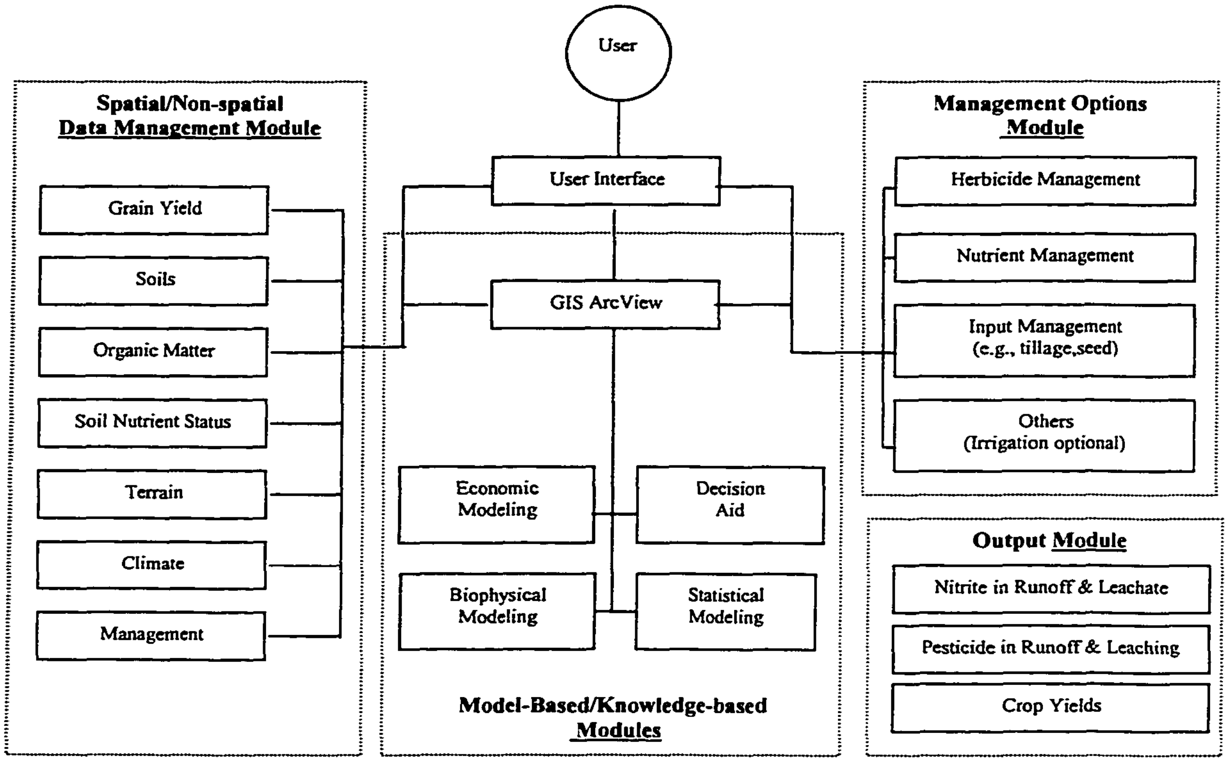

Figure 1. The Overall Structure of IDSS-PA

production practices. Similarly the modeling components facilitate evaluation of the effects of production management decisions (e.g., tillage, nutrient/pest management, etc.) and environmental impacts of production practices.

As with many spatial decision support systems, the current version of IDSS-PA consists of the following modules: (a) spatial and non-spatial data management module, (b) biophysical, statistical and economic modeling module, (c) a decision-aid or knowledge-based module, and (d) an intuitive user-interface module. Future version of this system will include a knowledge-based decision aid module, and an economic data visualization module. The data management module handles an extensive set of data relevant to the implementation of precision agriculture. It is designed to manipulate multiple level (farm, field and regional) data and supports data import or export from a variety of precision agriculture and GIS software, including SSToolbox (SST Development Group, Stillwater, OK), AgLink (Agrics Corp., Roswell, GA), and ArcView GIS (Environmental Systems Research Institute, Redlands, CA). Furthermore, this module also stores, manipulates, and manages climatologic data and field farm data collected using GPS and terrestrial space-based sensing techniques. A typical climatologic data can comprise of historical data describing the local climate and synthetic data generated through standard climate generators such as CLIGEN. The farm/field data describes the general crop production system and contains farm-specific prices for relevant inputs and outputs, landscape data describing the terrain and soils, and management data such as pesticide and nutrient application rates, crop scouting reports, and soil nutrient analysis.

The model-based module of IDSS-PA consists of biophysical modeling, multivariate spatial statistical analysis techniques, and other quantitative models that provide the system's analytical and pragmatic modeling capabilities. These analytical models and prognostic tools are fully coupled with the other modules within IDSS-PA. The biophysical models incorporated into IDSS-PA include the Root Zone Water Quality Model or RZWQM (USDA-ARS, 1992), one-dimensional and process-oriented model developed to simulate the physical, chemical, and biological processes within an agricultural field. The other biophysical model involves simulation of plant growth processes and biomass production by the CERES-Maize (Jones and Kiniry, 1986), a version of the integrated CROPGRO (Boote et al., 1996) that can be used to: optimize planting density, maturity type, fertilizer input and irrigation; determine which genetic traits would maximize yields and economize returns across terrain, soils and climate zones; predict how crops respond to climate, nutrients, water, light, and other conditions; and gain theoretical understanding of the crop production system (Kiniry et al., 1997; Boote et al., 1996). The CERES-Maize simulates the processes of soil-water balance, light interception by plant canopy, dry matter production, and the portioning of the above biomass into grain. The model simulates seed mass production from a potential seed growth rate, a degree-day sum required for grain filling, and the amount of assimilate available for grain growth. In IDSS-PA, the CERES-Maize model issued as an alternative to the generic plant growth model in the RZWQM. The economic model consists of an input-output model that estimates changes in management decisions and profits for a farm under site-specific management as opposed to a similar farm under conventional management. The model identifies the critical amount of variability that justifies a prescribed level of investment in precision agriculture technology and practices. Other analytical and optimization models incorporated into the model-based module are designed to enhance either the analysis or the summarization of data. For instance, the module incorporates prognostic models for creating farm input recommendations (e.g., lime and nutrient prescriptions) and S-PLUS statistical software that enhances interpolation and exploratory analysis of data. Data analysis capabilities of the IDSSPA range from simple univariate and bivariate analysis to more complex multivariate analysis of different data series.

The decision-aid and knowledge-based module of IDSS-PA provides assistance and support in making farm-level management decisions based on available data (simulated and measured). It is intended to meet the critical needs for a tool that not only facilitates the interpretation of the data from the decision-support system but also enhances the decision-making processes of the producer before, during, and after implementation of precision agriculture management. At the core of this module are heuristics and production rules provided by an expert system, as well as analytical processing and data mining tools that enhance the selection of practices that meet various ecological, economic, and agronomic constraints. This module also assists the user of IDSS-PA in routine, site-specific resource management decisions, such as fertilizer or herbicide application practices, and the selection of cropping practices that minimize production risks.

Communication between the user and the several interrelated modules within IDSS-PA is facilitated by the user interface, which not only emphasizes ease-of-use and accessibility, but also addresses desirable factors in human-computer interactions. Constituted on the basis of standard graphical user interface models that are based on the windows, icons, meanus, and pointers (WIMP) primitive, the IDSS-PA user interface module comprises of objects (pull-down menus and buttons) and dialogue boxes designed using C++ object-oriented programming languages and Avenue scripts. It is uniquely designed to accommodate various data representations required by the precision agriculture community, and contains operations, communication modalities, and integration paradigms that enable the user to interactively manage the data inputs and outputs in the form of dialogues or processes.

The spatial data analysis module of IDSS-PA combines the statistical analysis capabilities of S-Plus software (Mathsoft, Seattle, WA) with the graphical data analysis and display functions in ArcView GIS. S-Plus is probably one of the most widely used software for exploratory data analysis and contains statistical functions for data synthesis and data mining. It provides methodologies for testing of hypothesis, performing univariate, bivariate, and multivariate data analysis, and determining correlation in spatially distributed variables. The S-Plus/ArcView interface, developed by Mathsoft as a companion to the S-Plus statistical software package, greatly enhances the statistical analysis of spatially distributed data. In addition to the spatial data analysis conducted using S-Plus and S-Plus for ArcView, the ArcView GIS provides tools and functions for database manipulation, and data display. ArcView GIS is probably the most popular GIS software developed for the desktop environment. It contains many of the geoprocessing functions that facilitate development of enterprise-wide applications. With over 500,000 copies in use worldwide, ArcView GIS provides functions and extensions that support geographic analysis in many application areas including telecommunications, utilities, agriculture, defense, oil and gas exploration, health care, mining, transportation, environmental management, and many other areas. The ArcView's Spatial Analyst Extension and the 3-D Analyst Extension were used quite extensively in this study.

Figure 2 shows the general layout and the primary GUI of IDSS-PA, which adopts the look and feel of the ArcView GIS' GUI. At the top-level the GUI provides the overall management of the modeling session, from data organization through modeling to display of the results. The definition of field-level parameters, choice of models for simulation (e.g., desire to run the crop model alone or the RZWQM98), statistical analysis of basic and derived (modeled) data, creating data surfaces using standard interpolation routines, and evaluating management decisions are handled through a menu bar that is visible throughout the simulation session. Each pull-down menu option and panel hierarchy is customized for the specific activity. For example, if a user is interested in statistical analysis of the field data, then he/she can select the "S-Plus" item from the menu bar. This results in a pull-down menu providing different options and capabilities for statistical analysis. On the other hand, if the user desires to run the biophysical and economic models, then appropriate selection in the main panel would lead to a pull-down menu containing the desired model (see Figure 3).

The IDSS-PA GUI design provides the environment to configure the selected modeling since each type of model — biophysical (RZWQM98), plant growth (CERES-Maize) and economic — has a distinct sub-interface consisting of model-specific dialog boxes and radio-buttons for configuring instances of that model. For example, if a user is interested in evaluating the runoff and leaching of an agricultural chemical in the field, menu panels and dialog box interfaces will open prompting the user to define the input parameters required by RZWQM98. The values of input parameters are chosen against a series of constraints and rules to insure that they represent part of a valid set of run parameters for this model. Figure 4 illustrates the menu panel and interaction options for the RZWQM98 modeling.

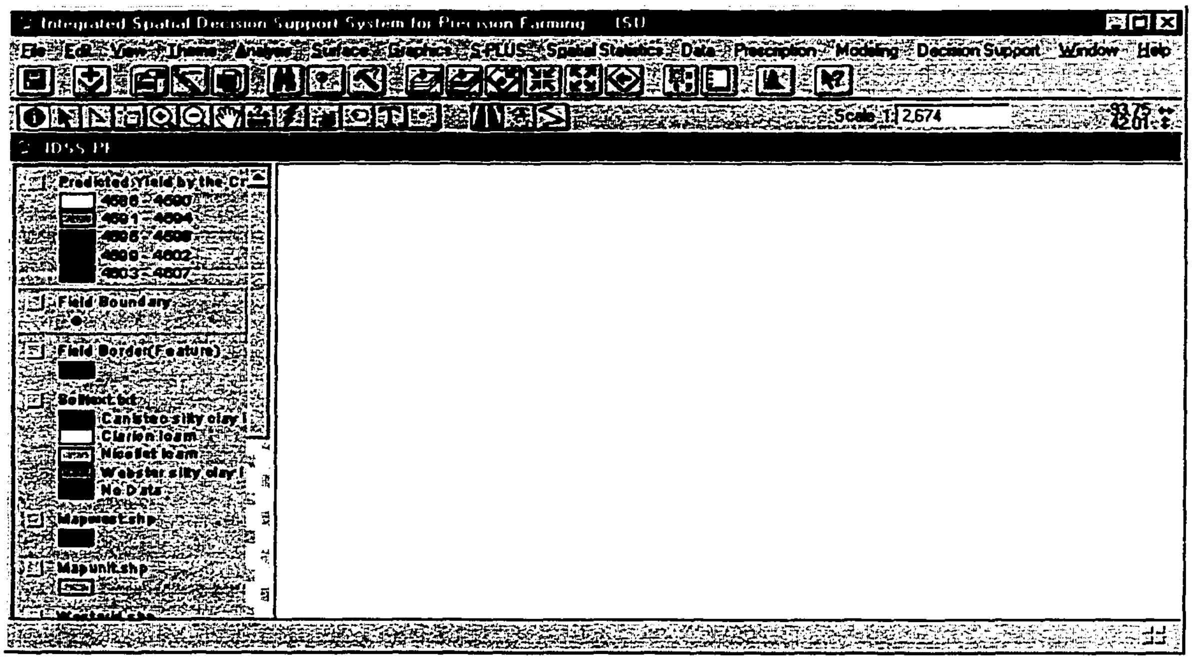

Figure 2. The General Layout of IDSS-PA

The IDSS-PA modeling environment provides many benefits to user. In addition to the ability to perform RZWQM98 model simulation on grid by grid basis, the modeling interface provide a comprehensive support for data and map exchange between popular precision agriculture software programs such as AgLink for Windows and SSToolbox. Users can import and export data between these systems and perform spatial statistical data analysis using S-Plus for ArcView GIS (see Figure 5). These capabilities for data integration and data analysis greatly reduces many of the problems associated with agriculture data as well as the integration of visual and computational analysis tools. A recurrent theme within the precision agriculture research community is the lack of interoperable software environments that integrate field data collected through sensors and intelligent implements with biophysical economic and statistical models to improve management decision make.

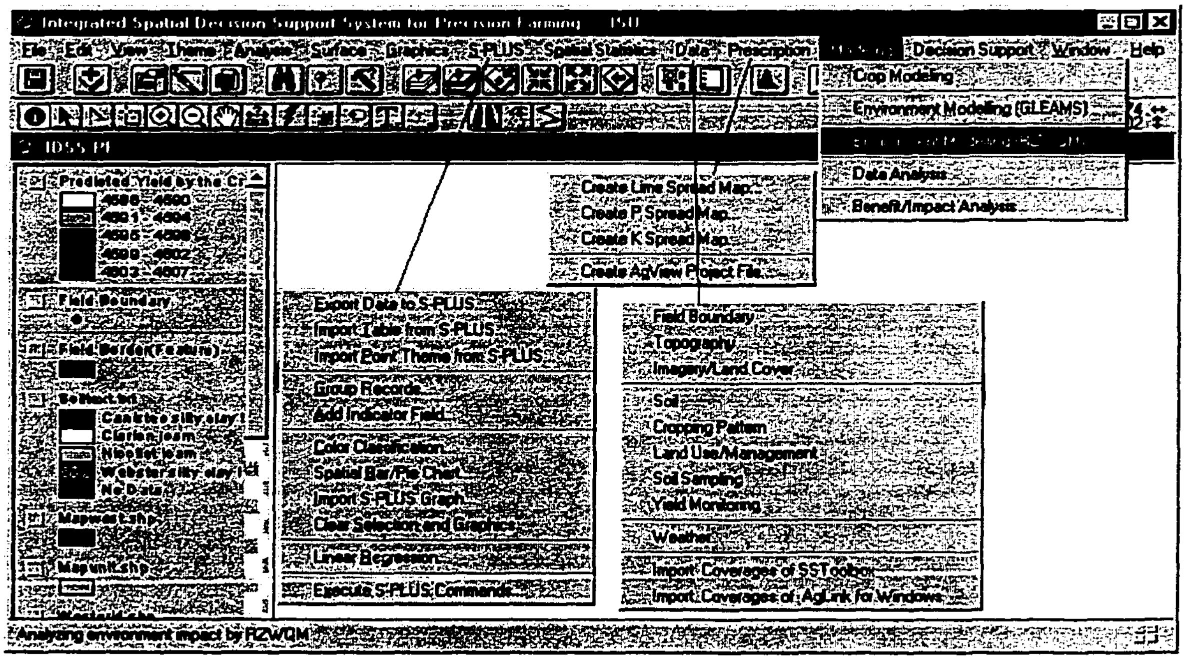

Figure 3. The Main Panel and Pull-down Menu of IDSS-PA

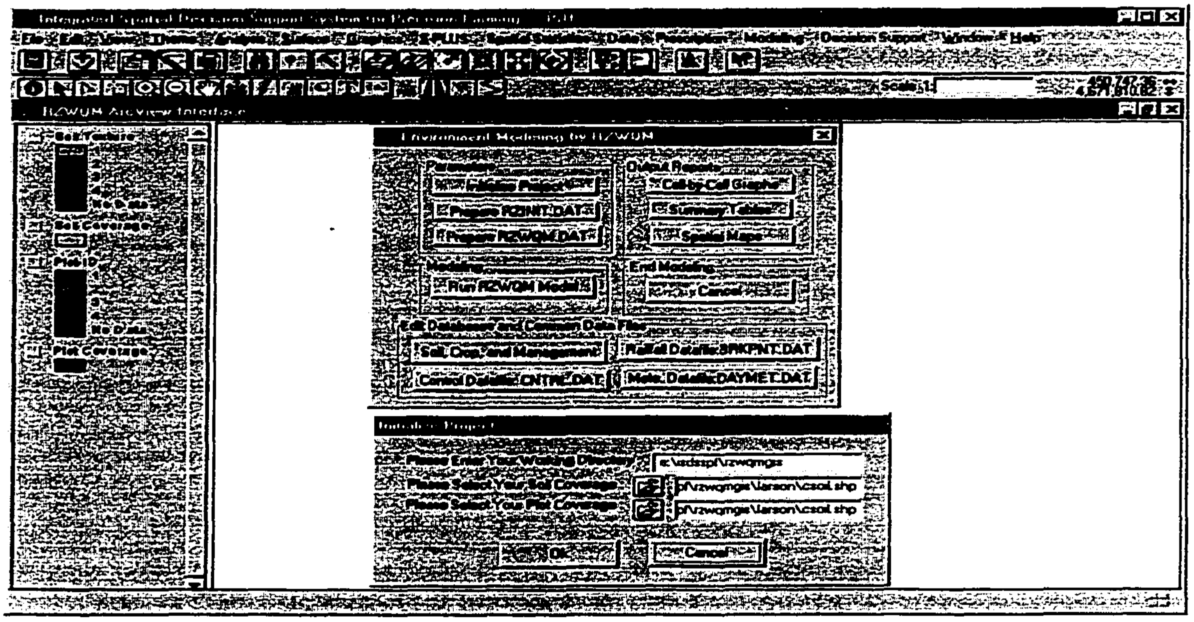

Figure 4. Interface to Configure Run Parameters for the RZWQM98

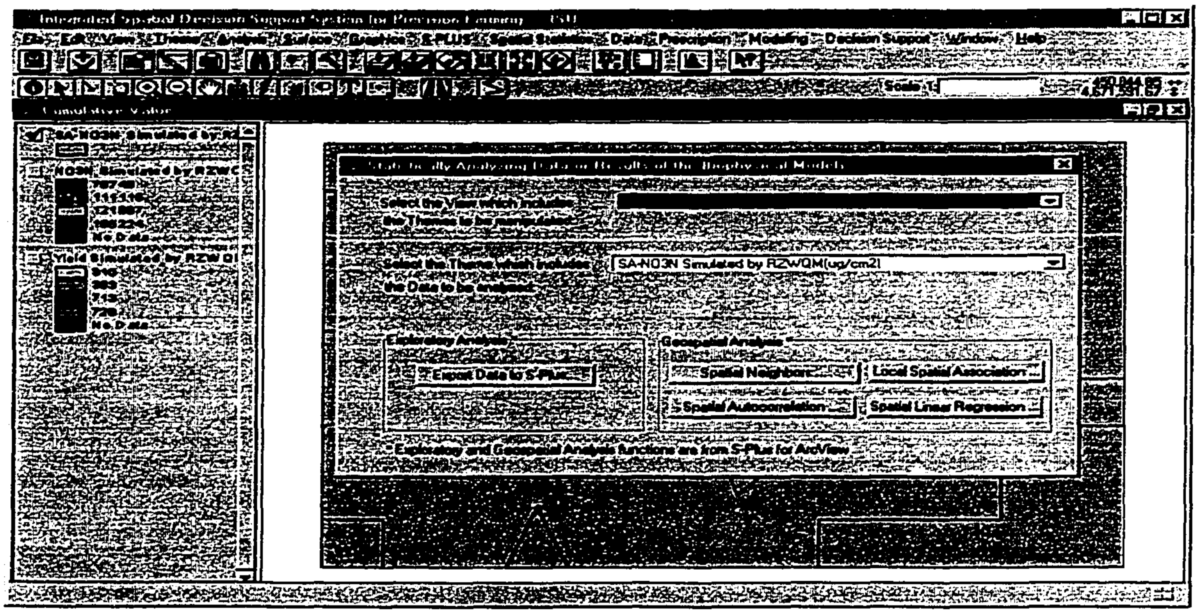

Figure 5. Interface to Perform Spatial Data Analysis

EXAMPLE APPLICATIONS

Characterize Variability of Yield and Nitrate-N Loss

This example application involved the use of IDSS-PA to organize data and predict grain yield and nitrogen loss in an agricultural field. The study area chosen is a 25-ha field located in Central Iowa.

Components of the decision support system are designed to provide a synergistic and seamless environment for evaluating sustainable production issues related to precision agriculture. As indicated previously, the database and data management module is uniquely constructed to be interoperable with standard precision farming and GIS software. Many of the data storage, manipulation, analysis, modeling, visualization, and decision-making functions required by the precision agriculture community industry are incorporated into the system. Figure 6 shows a typical result that can be derived by using the integrated decision support system. This result relates to the estimation of crop yield and nitrogen loss obtained from the biophysical model. As seen in Figure 6, the grid-based display of model results enhances integration of results with other data sets or coverages, and facilitates the incorporation of other derived GIS coverages such as remotely sensed imagery of nutrient or water deficit areas of the field.

Choose Reasonable Simulation Resolution

Coupled with ArcView GIS, the CERES-Maize model will run cell by cell and enable the user to consider field spatial variability. A field consisting of several different soils is subdivided into a number of smaller cells with homogenous soil properties and other crop parameters. Thus, Cell size affects rasterization results and the model inputs. A reasonable

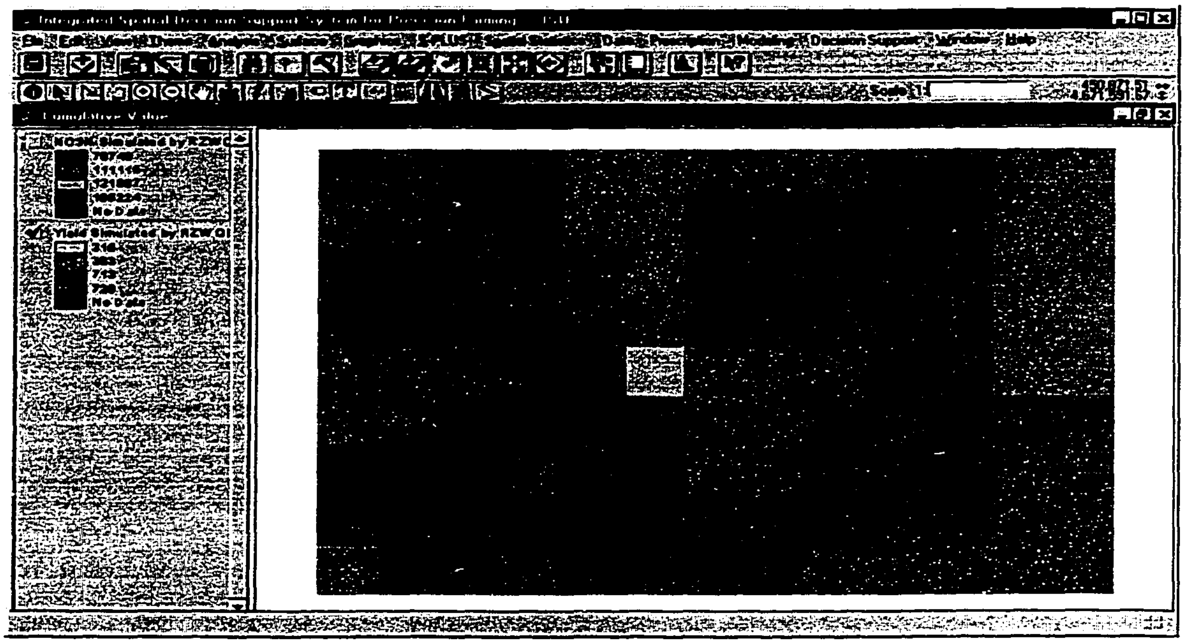

Fig. 6 Maps of Model-simulated Crop Yield (20×kg/ha) and Nitrate-N Loss (g/ha)

cell size should enable the information included in the field experiment data to be sufficiently used by the GIS-based CERES-Maize model. While, in the IDSS-PA, several interpolators including Kriging, IDW, and Spline can be used to subdivide the study field, they don not include any algorithm to help modelers decide a reasonable cell size for the study field. However, the user can do several-year simulations using the GIS-based CERES-Maize model for various cell sizes and then employ statistical module included in the IDSS-PA to find a reasonable simulation resolution.

Following two algorithms may be employed to determine the reasonable simulation resolution:

(1) The annual average yield simulated using the reasonable cell size should be higher than that simulated by treating the whole field as one large cell, i.e.,

$$\sum_{i=1}^{N}(\sum_{j=1}^{M}Y_{ij})/M)/N \geq (\sum_{i=1}^{N}Y_{i})/N$$

where, N = number of simulated years; M = number of this size cell; Y_{ij} = simulated yield for jth cell in ith year; Y_i = simulated yield treating the whole field as one large cell in ith year.

(2) The yield simulated using the reasonable cell size should have minimum standard error or variance, i.e.,

$$\min_k \sqrt{\frac{\sum_{i=1}^{N}[(\sum_{j=1}^{M} Y_{ij})/M - (\sum_{i=1}^{N}(\sum_{j=1}^{M} Y_{ij})/M)/N]^2}{N-1}}$$

where, k = number of cell sizes simulated.

The study field is the 32-acre west field of the Sorenson farm, located near Greene County, Iowa. The field consists of four soils, 8.0-acre Clarion Loam, 20.0-acre Canisteo Silty Clay Loam, 3.8-acre Webster Silty Clay Loam, and 0.2-acre Nicollet Loam. The Canisteo Silty Clay Loam soil is continuously distributed across the southern part of the field, whereas the Webster Silty Clay Loam soil across the northern part. The Nicollet Loam soil is bisected into two small areas, one of which is surrounded by the Canisteo Silty Clay Loam soil and another shares common borders with the Clarion Loam soil and the Webster Silty Clay Loam soil. There is a consistent border between the Webster Silty Clay Loam soil and the Canisteo Silty Clay Loam soil. In Spring 1997, soil properties including lower soil moisture, upper soil moisture, saturated soil moisture, soil bulk density, soil organic matter, and soil PH were surveyed in terms of the 64-grid sampling points. The results indicated that the field has a very high spatial variability.

Using 15-year weather data measured at Ames weather station, Iowa, the GIS-based CERES-Maize was run on five different cell sizes, 360m (whole field), 104m (4 rows × 3 columns), 61m (7 rows × 5 columns), 40m (10 rows × 8 columns), and 21m (20 rows × 15 columns). Table 1 gives the field average simulated yield for these 15 years. Compared with the simulated annual average yield of 4929 kg/ha by treating the whole field as one large cell, simulations using cell sizes of 40m and 61m gave slightly higher yield of 4931 kg/ha, but simulations using cell sizes of 21m and 104m lower yields of 4928kg/ha and 4929 kg/ha respectively. The simulated yield using 40-m cell size has smallest standard error of 1625 kg/ha. Thus, 40m may be the reasonable simulation resolution for the west field of the Sorenson farm.

Table 1 The Field Average Simulated Yield

Cell Size (m) Yield (kg/ha) Year	360 (whole field)	104 (4×3)	61 (7×5)	40 (10×8)	21 (20×15)
1	4907	4943	4912	4894	4907
2	3752	3758	3759	3752	3753
3	4766	4785	4783	4780	4784
4	6100	6105	6104	6107	6106
5	6646	6643	6643	6642	6643
6	4337	4369	4364	4389	4385
7	2271	2229	2233	2236	2235
8	6892	6887	6888	6885	6886
9	4379	4362	4362	4420	4359
10	4428	4417	4423	4420	4420
11	4635	4613	4616	4611	4612
12	7876	7875	7875	7875	7875
13	5972	5966	6021	5963	5963
14	1846	1849	1849	1848	1848
15	5133	5137	5137	5140	5140
Average	4929	4929	4931	4931	4928
Standard Error	1624	1628	1630	1625	1627

Note: The simulations were based on no irrigation and one pre-planting fertilizer application.

CONCLUSIONS

Precision agriculture is the term used to describe crop production practices and management strategies that maximize net farm income (through enhanced yield and reduced farm inputs) and minimize environmental pollution through site-specific variable-rate management of chemicals. Many in the industry contend that for precision agriculture to meet these sustainable production goals, new tools for effective and efficient decision making are needed. This paper describes the major components of a spatial decision support system designed to enhance data management, modeling, visualization, and decision making in precision agriculture. The Integrated Decision Support System for Precision Agriculture couples ArcView GIS, biophysical and economic models, spatial statistical models, expert or knowledge-based system and user interface. It can enhance understanding of agricultural systems by determining spatially referenced data, and improves analysis of the trade-off between economic returns and environmental quality. IDSSPA can be a useful research and decision-support tool for precision agriculture and naturai resource management.

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CHAPTER 3
EVALUATING THE ENVIRONMENTAL AND AGRONOMIC IMPLICATIONS OF VARIABLE-RATE NITROGEN MANAGEMENT

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Abstract:

Characterization of field spatial variability is requisite to enhancing the adoption implementation of precision agriculture practices, which is widely believed to maximize net farm income and to minimize potential environmental pollution problems through site-specific, variable-rate chemical management. If the characteristics of soil, terrain and management parameters that represent field variability can be determined and spatially referenced by using the geographic information system (GIS), computer simulation modeling can be performed to document the potential impacts on yield and chemical losses. This paper describes the combination of information on field spatial variability with ArcView GIS and the Root Zone Water Quality Model (RZWQM) to evaluate agronomic and environmental implications of variable-rate management of nitrogen (N) in a 25-ha field located in central Iowa. All of these components were integrated within a problem-solving environment that utilizes client-server architecture and recent advancements in graphical user interface. In this study, the agronomic implications of variable-rate N management is assessed in terms of measured and predicted yields, while the associated environmental impacts are evaluated from nitrate-N leaching losses. The statistical components-of-variance model was employed as a data-mining technique to enhance interpretation of both the observed and predicted data.

The results of the study clearly show the benefits of variable-rate N management in reducing potential nitrate-N leaching losses.

Keywords: Precision agriculture, site-specific management, GIS, RZWQM, statistical modeling, variable-rate application, nitrogen

1. INTRODUCTION

Excessive application of plant nutrients and pesticides on agricultural land has resulted in both environmental degradation and economic loss to the farming community. In a 1996 National Water Quality Assessment Report to Congress, the U.S. Environmental Protection Agency (EPA) concluded that, despite significant progress made during the last several decades to control non-point pollution, significant water quality problems persist throughout the country (EPA, 1997). Using state reported water quality survey, the EPA noted that: (1) 36% of the rivers and streams surveyed, including 55% of all perennial stream miles, were partially or fully impaired with another 8% of the rivers and streams threatened; (2) 39% of surveyed lakes were partially or fully impaired with another 10% threatened; and (3) 38% of the estuaries surveyed were impaired with another 4% threatened. In addition, about 15,000 watersheds across the country were identified as either not meeting water quality standards or not failing to meet expected uses (EPA, 1997). Agricultural non-point source pollution was cited as the primary source of the water quality problems in many areas of the country.

Environmental concerns resulting from agricultural non-point source pollution has placed demands on farmers and ranchers to implement management practices, such as conservation tillage, integrated pest management and nutrient management to reduce the delivery of pollutants to streams and aquifers. Precision agriculture, a relatively recent crop production and agricultural management strategy holds great promise to minimize environmental pollution while maximizing economic productivity and profitability. However, for precision agriculture to move forward and meet expected goals, field experiment, across all levels of spatial arrangements (e.g., plots, whole farm, and watersheds) is needed to collect the reliable data to quantify and characterize chemical fate and transport in agricultural systems and to develop effective management strategies. In parallel, computer simulation models and decision support systems are needed to not only provide the analytical tools for evaluating the environmental impacts of different agricultural management practices (Kumar et al., 1998), but also assist producers in making long-range strategic production decisions. These decision support systems, when adequately validated under various climatic, soil and management regimes, provide efficient problem-solving environment wit which to analyze potential environmental implications of precision agriculture practices. Furthermore decision support systems can also improve the mining and interpretation of data from field experiment, assist in the analysis and characterization of production and economic risks, and support development and assessment of environmental policy decisions (General Accounting Office, 1982).

Precision agriculture requires modification of production practices and methods to reduce leaching losses of chemical inputs. Variable rate application technology and the site-specific application of crop production inputs (e.g., irrigation water and seeds) provide an opportunity to enhance crop production efficiency and improve environmental quality.

Because variable-rate application (VRA) of fertilizer, herbicide, and other agronomic inputs is central to precision agriculture, many investigators have examined its potential impacts on crop yields. Many other studies have utilized computer simulation models to document the potential environmental and natural resource of VRA (Fiez et al., 1995; Larson et al., 1997; Khakural et al., 1994; Mulla et al., 1994). Delgado (1998) evaluated the potentials of the Nitrogen Leaching Evaluation of Agricultural Production (NLEAP) model to assess impact of variation in soil type on residual nitrate-nitrogen (NO_3-N). They also tested the ability of NLEAP to provide an analytical tool for evaluating impacts of precision agriculture management. Paz et al. (1999) used a generic crop growth model to determine yield variability under variable-rate nitrogen (N) application in a 16-ha corn field. Watkins et al. (1999) used the Environmental Policy Integrated Climate (EPIC) model to predict crop yields and N losses for different parts of a 63-ha field under conventional and variable application of N fertilizer. Based on the conditions of their study, variable-rate application of N did not provide a noticeable difference in the levels of N loss from the field, when compared to conventional, uniform N application. Larson et al. (1997) used LEACHN model (Wagenet and Hutson, 1992) to estimate the amount of inorganic N leached below the 1-m soil depth under uniform and site-specific management of N fertilizer. Overall, these previous studies show mixed results regarding the environmental benefits of variable-rate technology. While many studies have shown, for example, runoff and leaching losses of NO_3-N from field-sized areas to reduce under variable rate N fertilization, other studies have shown these losses to remain the same as in conventional, uniform management strategy. To date, the environmental and water quality benefits of variable-rate application of crop inputs have yet to be fully established.

While existing computer simulation models provide robust analytical tools to predict the agronomic and water quality implications of precision agriculture, many users have found these tools to be not only demanding in terms of data inputs, but also limiting in many precision agriculture applications. For example, there is a gap between models developed to evaluate plot- or field-scale water flow and chemical transport and those that can be used for assessing impacts of site-specific crop production management decisions. Many scientists and researchers in the agribusiness demand models and decision support systems that incorporate spatial variability and allow effective manipulation, mining, and display of large amounts of field data that describe interrelated agronomic, socioeconomic and environmental factors. Policy-makers and resource planners demand user-friendly and interactive tools for data synthesis, data interpretation and for effective, technically defensible policy decisions. Local stakeholders, particularly farmers, require an easily accessible and user-friendly tool to plan tactical and strategic management decisions that improve profitability and reduce adverse effects of these practices. Given the need of these constituencies, an interactive problem-solving environment and decision support system are needed. This paper describes components of a problem-solving environment and decision support system for evaluating the agronomic and water quality implications of variable rate application of crop production inputs. It also details an example application of the modeling environment and decision support system in a 25-ha corn-soybean field. The problem-solving environment and decision support system integrate ArcView GIS, CERES-Maize plant growth model, RZWQM98 water quality model, and S-Plus statistical analysis software package. The remaining of this paper is organized as follows. First, the components of the problem-solving environment and decision support system are presented. Then, the details of the field experimentation and example application of the system to evaluate crop yield and nitrate-N leaching losses within the field are described. This section is followed by a brief discussion of the issues related to the use of field-scale chemical fate and transport models in precision agriculture, particularly to evaluate the implications of variable-rate nutrient and pesticide management. In this study, we define a problem-solving environment as an environment which encapsulates the various geospatial and statistical analysis components, databases, and simulation modeling within an integrated interactive graphical user interface that reduces the evaluation of "what if?" scenarios.

2. METHODS AND MATERIALS

2.1 Problem-solving Environment: Overview

As stated previously, computer models for predicting fate and transport of chemicals in the agricultural ecosystem offer efficient analytical tools to generate valuable information on impacts of agricultural management practices. The use of these tools greatly eliminates the need for extensive, time-consuming, and often costly field experimentation. However, performing simulations using these models, especially by an inexperienced and novice user, requires specialized expertise in not only understanding how the computer code works, but also the hydrological water quality limitations of the model in a specific application area. Some novice users of field-scale models consider them to be overly complex, lack user interactivity, and require large amounts of data. Recent advances in problem-solving environments, GIS, decision support system, and graphical user interfaces have significantly changed the nature and art of computer modeling. In particular, problem-solving environments and decision support system provide an integrated and interactive environment for running computer models. These generally incorporate facilities and tools to assist the user in formulating problems, manipulating large database to extract relevant data for modeling, and enhance interpretation of results. They also provide advanced modeling and analytical functions that improve integration and management of information from diverse sources and provide support structure to enable resource managers make technically defensible and scientifically balanced management decisions. This modeling environment was uniquely designed to enhance interoperability with other system components including databases, environmental models, and decision-making components provided by an expert or knowledge-based system. The design philosophy was to provide the user with as much ease as possible in (1) setting up the modeling conditions such as the number of grid cell within a field, (2) executing the model for individual grid cells and performing process routing, and (3) analyzing the model results.

2.2 Biophysical Modeling: Root Zone Water Quality Modeling

The biophysical modeling component of the problem-solving environment and decision support system consist of two widely used process-based models, including the Root Zone water Quality Model (RZWQM) and the Ceres Maize Plant growth model. The latter was used to provide a more process-oriented and phonological-base simulation of plant growth processes and biomass production. Root Zone Water Quality Model (RZWQM) is a physically based, lumped, and field-scale model that incorporates the important physical, chemical, biological, physiological, and management processes of an agricultural system (USDA, 1992a). The model consists of water, chemical, and heat transport modules; a plant growth module; an evapotraspiration module; a chemical (nitrogen, phosphorus, and pesticide) module; an organic matter cycling module; and a management practice module. In each module, process-oriented equations are used to describe the associated fate and transport processes and mechanisms.

Like most process-oriented field-scale models, RZWQM requires many input parameters related to climate, soil, terrain, and management. The primary climate data required by the model include daily minimum and maximum air temperatures and the breakpoint daily precipitation. Soil properties include bulk density, porosity, field capacity, percent sand, silt, and clay content, and hydraulic conductivity. Management data consists of tillage, nutrient application rates, strategies for nutrient application, and amount of surface residue cover. These management parameters are readily obtained from farmers and records.

The reliability of RZWQM has been established in a number of applications. Detailed calibration and validation of RZWQM has been presented by Bakhsh et al. (1999), Ma et al. (1995), Ahuja et al. (1996),Singh et al. (1996), and Azevedo et al. (1997). These reliability tests have shown the model to provide very reliable estimates of chemical transport in agricultural systems under different management regimes. The recently Windows-based user interface enhancements to the model significantly improves data input preparation, choice of modeling options, and synthesis and manipulation of model outputs.

The problem-solving environment and decision support system also contains an improved process-based module for predicting impacts of agricultural management, meteorological and genetic variables, and soil characteristics on plant growth. In the system, enhanced prediction of growth and yield of corn is provided by the Crop Eunonaunt Resources Synthesis or Ceres-Maize model (Jones and Kiniry, 1986). The model not only predicts growth and yield of corn but also the development of the plant as impacted by natural and anthropogenic factors. The Ceres-Model has been used in a wide range of studies to simulate crop growth at a plot and field-scales (Garrison, 1998; Kiniry et al., 1992; Keating et al., 1988; Kiniry and Knievel, 1995). The primary model inputs include management practices (e.g., tillage; row spacing; variety; plant population; fertilizer and irrigation application rates, timing, and methods), and environmental conditions (e.g., daily precipitation, solar radiation, relative humidity, daily minimum and maximum temperature, and soil hydrologic properities).

2.3 Geographic Analysis: ArcView GIS

At the heart of the problem-solving environment and decision support system is an interactive data manipulation, analysis, and display module provided by ArcView GIS. Developed and marketed by the Environmental Systems Research Institute (Redlands, CA). Developed primarily for desktop mapping and geographic data analysis and display, ArcView is perhaps the most widely used GIS software in the marketplace. With an estimated 500,000 copies in use worldwide, ArcView provides users an intuitive, easy-to-use, point-and-click interfaces for manipulating, querying, analyzing, modeling, and visualizing data from many different sources. It contains task wizards and customized programs (e.g., Dialog Designer) that allow users to quickly develop customized, enterprise-level applications and interfaces by adding standardized functions and operations, deleting and adding buttons, and attaching a script to automate a process. ArcView GIS also contains customized modules, called Extensions, for enhancing the process of modeling, visualizion, and mining of data. For example, as advanced extensions, the Spatial Analyst Extension and the 3D Analyst Extension, when used with ArcView, provide even more powerful functions and tools to analyze and solve real-world problems. In particular, the Spatial Analyst Extension provides needed capabilities and functions for spatial modeling via tools that allow users to: (1) create, query, and analyze cell-based data, (2) perform integrated vector-raster analysis using feature-based and grid-based functions, and (3) construct grid-based spatial models through the use of ModelBuilder. The Spatial Analyst Extension also contains functions that allow users to: (1) create continuous surfaces from point features; (2) perform discrete cell-by-cell analysis; (3) conduct local, focal, zonal or global analysis on point data to, for example, generate input data or terrain attributes such as aspect and slope; (4) perform hydrological analysis using cell-level digital elevation model; and (5) display basic and derived data in various formats. The ArcView 3D Analyst Extension provides a suite of tools and functions to create three-dimensional surface models, model real-world surfaces and subsurface features, and perform interactive visualization of data. Other ArcView GIS Extensions include Network Analyst, StreetMap, Business Analyst, Image Analyst, Tracking Analyst, and Internet Map Server for publishing dynamic maps on the World Wide Web.

2.4 Statistical Data Analysis: S-Plus

The critical role of spatial location within an agricultural field or landscape has profound and far-reaching implications on the agronomic (e.g., crop yield) and environmental response (e.g., nitrate runoff and leaching). Indeed, spatial location, in addition to being an important factor in precision agriculture, can lead to two different types of spatial effects: spatial dependence (e.g., spatial autocorrelation) and spatial heterogeneity. In precision agriculture, particularly in the broad areas of site-specific crop production, spatial dependence can lead to a variety of measurement problems (e.g., presence of spatial externalities and arbitrary delineation of spatial units for observation and sampling) and could present unique challenges for conventional univariate and aspatial summarization of results. Spatial heterogeneity, according to Auselin (1994), relates to spatial differentiation due to the intrinsic uniqueness and location within the agricultural field. To elucidate influence of spatial dependence and spatial heterogeneity and to enhance visualization and interpretation of results, a statistical analysis software package (S-Plus) was integrated into the problem-solving environment.

S-Plus (Mathsoft Inc, Seattle, WA) is a premiere spatial and aspatial data analysis package that provides an interactive environment for data analysis and statistical data mining capabilities. With over 3800 built-in statistical functions and graphic models, S-Plus provides highly sophisticated techniques and models for exploratory data analysis and data summarization. It contains elegant, object-oriented graphical user interfaces for data import and export, spatial statistical data analysis, and advanced data modeling.

3. EXAMPLE APPLICATION

3.1 Study Area and Field Experiment

The study area to demonstrate and validate the utility of the problem-solving environment is a 25-ha row-crop field located in Story City, near Ames, Iowa. As with most agricultural lands in central Iowa, the field is drained using nine subsurface tile drains, with each tile flowing into individual sumps. Each sump is equipped with an automatic flow recorder that monitors subsurface drainage flow on a daily basis. The water samples collected from each sump were analyzed for NO_3-N concentration. Three nitrogen (N) treatments were applied under a randomized design with three applications. The area drained by one tile line represents one treatment plot (or treatment replication). During 1998, when corn was planted at the study site, plots 1, 4, and 9 received 172 kg/ha of N-fertilizer, plots 2, 5, and 8 received

115 kg/ha, while plots 3, 6, 7 received 57 kg/ha of N-fertilizer. Corn yields were measured using a Case IH combine harvester equipped with differential global positioning system (DGPS) receiver and a yield monitor. Primary tillage consists of moldboard plow performed after harvesting the crop, while secondary tillage consisted of two field cultivations, performed before planting and during the crop development stage.

3.2 Model Calibration and Modeling Database

The N-fertilizer application rate of 172 kg/ha and the model parameters averaged cross the plots 1, 4, and 9 are used to calibrate RZWQM by comparing the predicted with observed tile flow and N concentration in the tile flow of these three plots. Figure 1 and 2 show the predicted and observed tile flow and N concentration in the tile flow respectively.

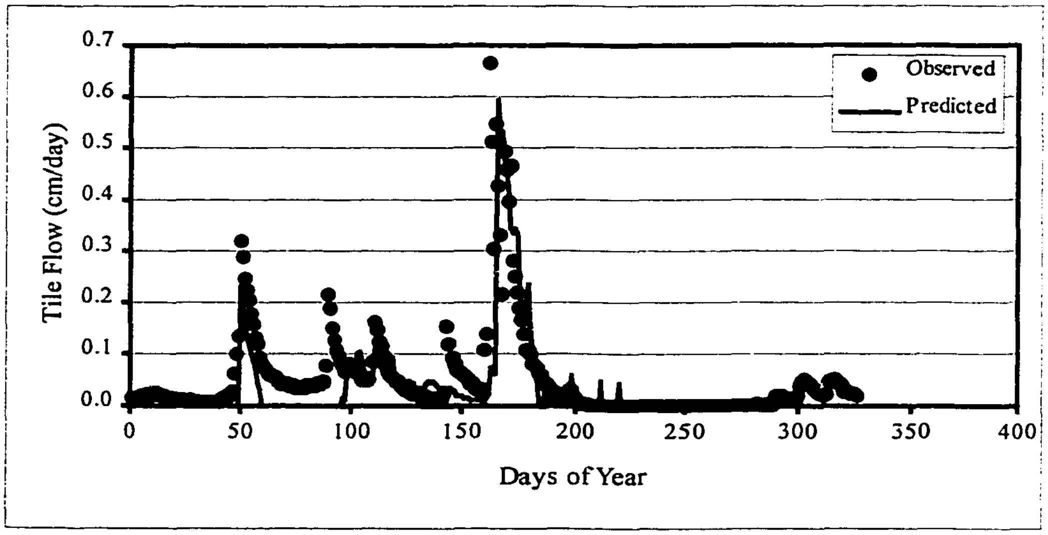

Figure 1 Comparison of the Observed and Predicted Tile Flow in 1998

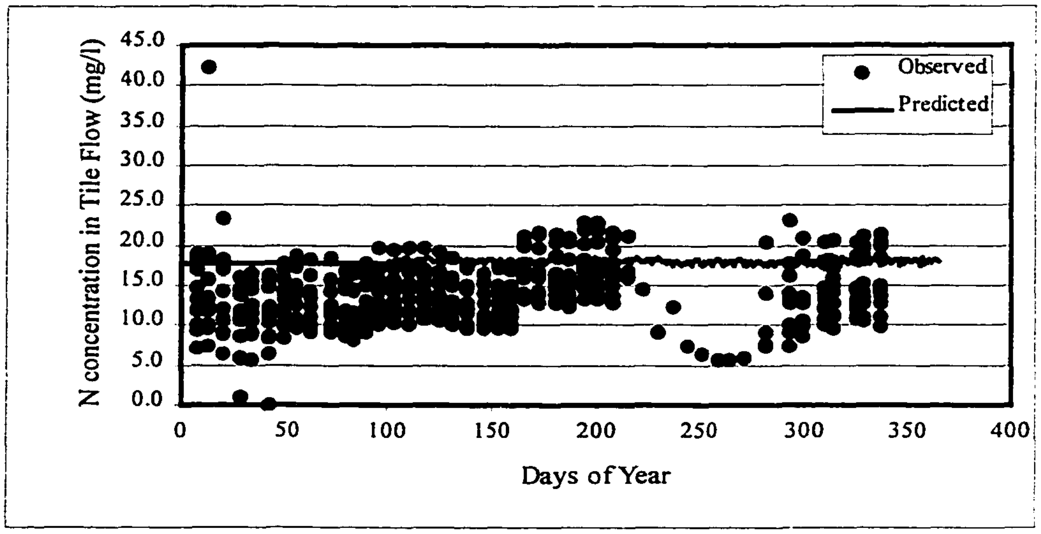

Figure 2 Comparison of the Observed and Predicted N Concentration in the 1998 Tile Flow

Relevant digital data describing the study area were imported into and organized by the ArcView GIS software (version 3.1). Using the field boundary map, the field was subdivided into 117 uniform grid cells or management units with unique properties. Data layer representing individual input parameters required by RZWQM were created using the Spatial Analyst Extension of ArcView. These data layers were created by using, for example, soil properties data. Measured at the 42 sampling locations within the study area (Figure 3), data layers representing field management conditions (e.g., tillage, chemical applications) were created according to existing field. Furthermore, residual and plant-required soil N maps were created as required. The individual spatial and non-spatial data required to implement RZWQM were organized and managed by ArcView GIS software. All of these processes were realized by the graphic user interface (GUI) built in Avenue. The calibrated RZWQM was run cell-by-cell to simulate corn yield and nitrate-N loss under various N-fertilizer application rates.

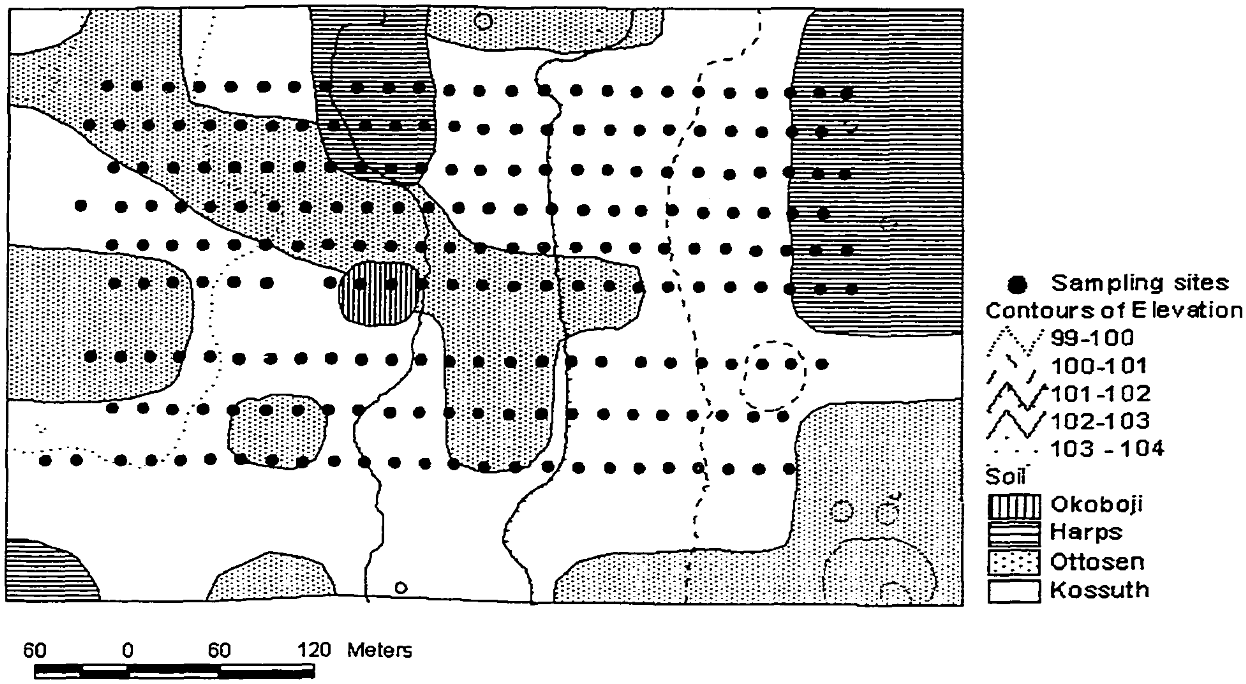

Figure 3 Soil Type and Topography of the Study Area with Data Sampling Sites

4. RESULTS AND DISSCUSION

4.1 Crop Yields and Nitrate Losses

The corn yield was measured at the 42 sampling points shown in Figure 3. The soil average yield is computed and is reported in Table 1. But, the NO_3-N losses were measured through the tiles draining water from each of the 9 strips. Each of the strips may consist of more than one type of soils. Thus the field average NO_3-N losses are reported in Table 2. Table 1 and 2 also show the predicted corn yield and NO_3-N losses for the four soils under various experimental and arbitrary N-fertilizer application rates. From Table 1, the model tends to under predict yield for the low application rates but over predict yield for the high application rates. The prediction error may range from –12 % for the Harps soil to 34% for the Okoboji soil. The reason may be that the Okoboji soil is poorly drained and the model

Table 1 Predicted and Measured Corn Yield (kg/ha)

Soil \ N Rate (kg/ha)	50	57	115	150	172	200	300	$Y_{i.}$
Harps	7676.1	8013.0 (9155.2)	10299.9 (10519.0)	11244.6	11500.5 (10174.6)	12026.3	11582.1	10140.3
Kossuth	7468.1	7967.7 (8595.7)	13067.9 (12517.5)	14361.6	12313.4 (10845.1)	11952.2	11474.3	11048.6
Okoboji	9636.0	7972.0	12247.0	13709.0	11960.7 (8904.7)	11854.0	13958.0	11562.7
Ottosen	8081.3	7978.6 (8643.5)	10787.9 (10461.9)	12548.0	11865.9 (9571.2)	11604.2	15013.8	11002.3
$Y_{.j}$	7706.9	7977.3	11970.7	13364.8		11852.3	12619.8	10915.29

Note: 1. $Y_{.j}$ and $Y_{i.}$ are yield averages by soil and N-fertilizer application rate respectively.
2. The values in ( ) are measured yield.

Table 2 Predicted and Measured NO_3-N Loss (kg/ha)

Soil \ N Rate (kg/ha)	50	57	115	150	172	200	300	$N_{i.}$
Harps	53.00	53.10	53.70	54.10	54.30	54.50	55.00	53.90
Kossuth	41.90	42.20	46.90	30.60	45.8	43.60	41.04	41.04
Okoboji	1.95	1.90	1.87	1.81	1.83	1.84	1.81	1.86
Ottosen	55.50	45.00	43.30	55.55	61.8	45.50	70.00	52.47
$N_{.j}$	47.33	44.21 (37.2)	46.31 (41.7)	41.35	51.60 (56.9)	45.32	51.68	46.03

Note: 1. $N_{.j}$ and $N_{i.}$ are NO_3-N averages by soil and N-fertilizer application rate respectively.
2. The values in ( ) are measured NO_3-N losses.

does not work well for such kind of soil. From Table 2, the model predicted NO_3-N loss well, and may give more accurate prediction for the high application rates than for the low application rates.

4.2 Statistical Data Analysis

Both yield and NO_3-N loss can be partitioned into four parts: mean, variance due to soil, variance due to N-fertilizer application rate, and random noise (variance due to other elements), i.e.:

$$Y_{ij} = \mu_Y + \tau_{Y1} + \tau_{Y2} + \varepsilon_{Yij} \quad (1)$$

$$N_{ij} = \mu_N + \tau_{N1} + \tau_{N2} + \varepsilon_{Nij} \quad (2)$$

where, i, j are soil and N-fertilizer application rate respectively; Y is yield; N is NO_3-N; μ denotes mean; τ denotes variances due to soil or fertilizer application rate; ε denotes random noise.

$$\mu_Y = \frac{1}{n_f \sum_{i=1}^{n_s} A_i}\left[\sum_{j=1}^{n_f}\sum_{i=1}^{n_s}(A_i Y_{ij})\right] \tag{3}$$

$$\mu_N = \frac{1}{n_f \sum_{i=1}^{n_s} A_i}\left[\sum_{j=1}^{n_f}\sum_{i=1}^{n_s}(A_i N_{ij})\right] \tag{4}$$

$$\tau_{Y1} = Y_{ij} - Y_{.j} \tag{5}$$

$$\tau_{N1} = N_{ij} - N_{.j} \tag{6}$$

$$\tau_{Y2} = Y_{ij} - Y_{i.} \tag{7}$$

$$\tau_{N2} = N_{ij} - N_{i.} \tag{8}$$

where, n_s and n_f are numbers of soil type and N-fertilizer application rate respectively; A_i is area of soil i; $Y_{.j}$ and $N_{.j}$ are averages by soil; $Y_{i.}$ and $N_{i.}$ are averages by N-fertilizer application rate.

Using S-Plus, the generalized linear models were fitted to the predicted values in Table 1 and 2:

$$\mu_Y = 10915.29 \tag{9}$$

$$\mu_N = 46.03 \tag{10}$$

$$\tau_{Y1} = 86.99 - 861.95x_1 + 46.35x_2 + 560.39x_3 \tag{11}$$

$$\tau_{N1} = 6.43 + 1.43x_1 - 11.43x_2 - 50.60x_3 \tag{12}$$

$$\tau_{Y2} = -5899.48 + 68.97x_5 - 0.14x_5^2 \tag{13}$$

$$\tau_{N2} = -2.49 + 0.017x_5 \tag{14}$$

where, x_1, x_2, x_3, x_4 are dummy variables and defined as follows:

$$x_1 = \begin{cases} 1 & \text{for Harps soil} \\ 0 & \text{for others} \end{cases} \tag{15}$$

$$x_2 = \begin{cases} 1 & \text{for Kossuth soil} \\ 0 & \text{for others} \end{cases} \tag{16}$$

$$x_3 = \begin{cases} 1 & \text{for Okoboji soil} \\ 0 & \text{for others} \end{cases} \tag{17}$$

and x_5 is N-fertilizer application rate.

Figure 3 and 4 show the QQ Normal plots of ε_{Yij} and ε_{Nij} respectively. It can be seen ε_{Yij} and ε_{Nij} are approximately normally distributed. Thus, the models (1) and (2) are held for the predicted yield and NO_3-N loss.

From Equations (11), Harps soil tends to give yield lower than the field average yield whereas other three soils including Ottosen, Kossuth and Okoboji may have yield above the field average value. And Okoboji soil contributes most to the yield variance due to soil. On the other hand, Harps and Ottosen soils tend to increase NO_3-N loss, and Kossuth soil and Okoboji soil decrease NO_3-N loss. Compared with Harps and Kossuth, Okoboji soil is most negatively correlated with NO_3-N loss due to its poor drain property.

From Equations (13) and (14), NO_3-N seems continuously to increase with N-fertilizer application rate slowly, whereas there exists an application rate at which yield variance due to N-fertilizer application rate reaches its peak. Taking derivative to Equation (13), we can get this N-fertilizer application rate of 246.3 kg/ha, at which $\max(\tau_{Yl}) = 2594.9$ kg/ha.

If the peak N-fertilizer application rate of 246.3 kg/ha is applied, the yields of Harps, Kossuth, Okoboji, and Ottosen will be 12735.2 kg/ha, 13643.5 kg/ha, 14157.6 kg/ha, and 13510.2 kg/ha respectively, whereas the NO_3-N losses be 55.59 kg/ha, 42.73 kg/ha, 3.56 kg/ha, and 47.73 kg/ha respectively. For 1998 weather condition, we can put more nitrogen fertilizer in Ottosen soil and give up Okoboji soil. The similar conclusion can be made by analyzing the measured yield data (Bakhsh et al., 1999).

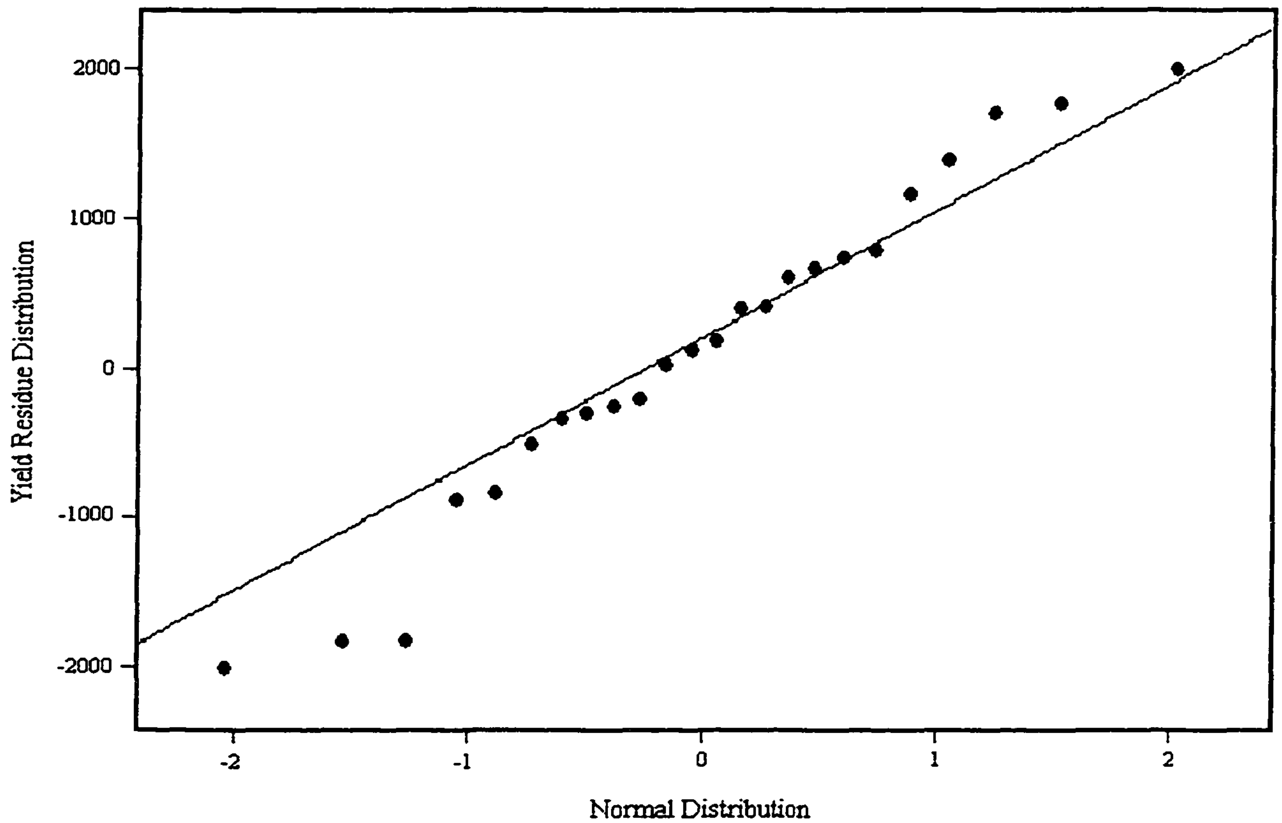

Fig. 3 QQ Normal Plot of ε'_{Yij}

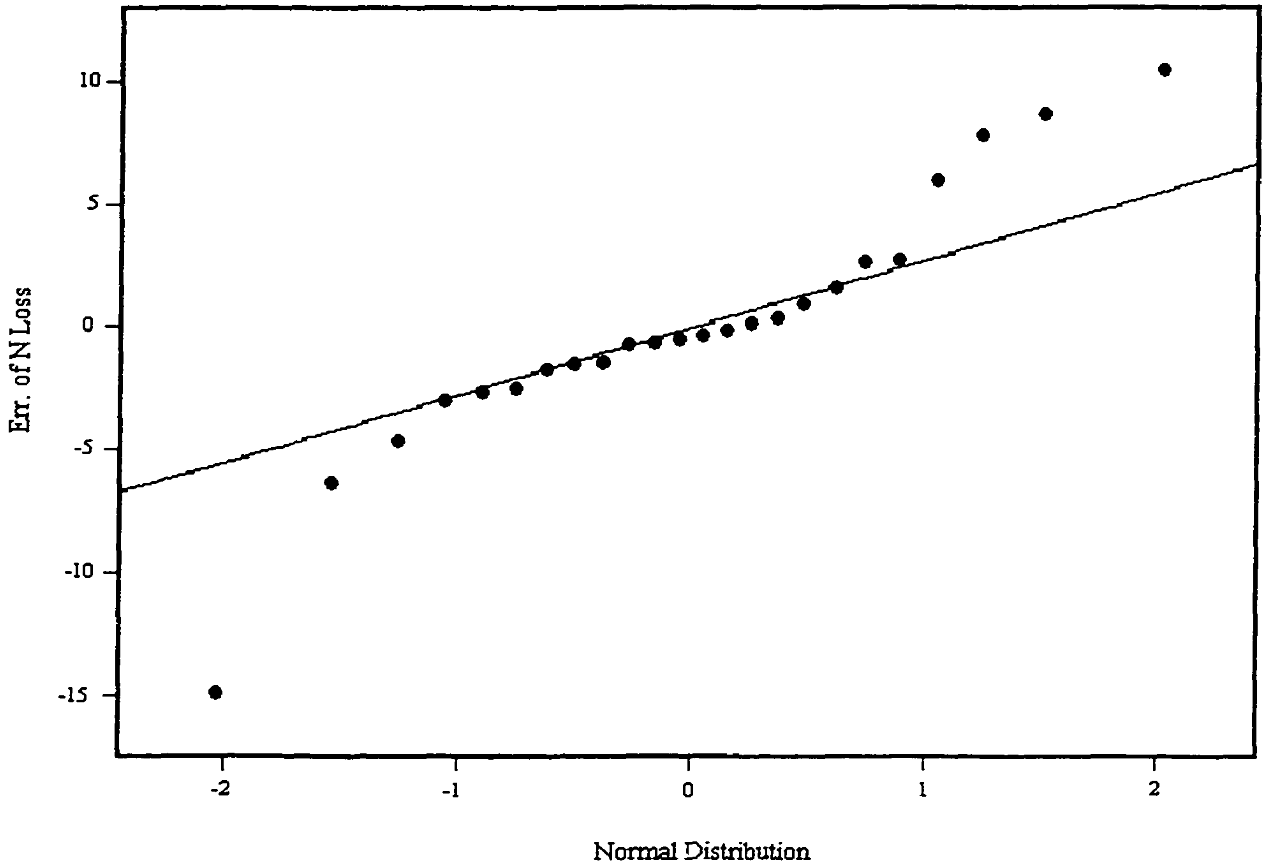

Fig. 4 QQ Normal Plot of ε'_{Nij}

4.3 Application of the Results

The results obtained from this component of the study may be used as follows:

Estimate the yield and NO_3-N loss for different soil with various N-fertilizer application rates without running RZWQM, which requires abundant filed experiment data and has several sophisticated input files need to be prepared. The results derived above only require soil type and N-fertilizer application rate as inputs.

Optimize nitrogen application in farm fields. Fertilizer should be applied in the soil producing most and having possibly little negative environmental impacts. For Larson Field, in terms of yield, fertilizer should be applied by the order of Ottosen, Haps, Kossuth, and Okoboji, however, in terms of NO_3-N loss, the application order should be Okoboji, Kossuth, Ottosen, and Haps. According to the principles of precision agriculture, multiple objectives, yield and environment, should be taken into account simultaneously. The multiple-objective rule recommended Kossuth, Ottosen, Haps, and Okoboji as the compromised N-fertilizer application order.

5. CONCLUSIONS

GIS-based RZWQM can account for filed variability. It can be used to analyze environmental and agronomic impacts of filed spatial variability with variable-rate nitrogen rates. The statistical components-of-variance model was employed to further interpret the simulation results. These results can be used to conveniently estimate the yield and NO_3-N loss under various conditions without running RZWQM, and to find the optimal N-fertilizer application order in terms of soil. The analyses showed that the peak N-fertilizer application rate is approximately 246.3 kg/ha. For Larson Field, according multiple-objective rule, the compromised N-fertilizer application order may be Kossuth, Ottosen, Harps, and Okoboji.

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CHAPTER 4
EXPLORING THE IMPLICATIONS OF SOIL NO_3-N

A paper to be submitted to the Agriculture and Environment

Xixi Wang and U.Sunday Tim

ABSTRACT: Soil NO_3-N may be not only a nutrient source for crops but also a potential non-point pollution source for environment. However, its content is affected by various factors. Taking three-year data measured in a 25-ha row-crop field, this paper employed exploratory data analysis and statistical MANOVA model to study the interwoven effects of N fertilizer application rate, soil depth, and year (representing climate and cultural practices) on the soil NO_3-N level. The results indicated that these effects may be additive. Furthermore, a multivariate linear regression model, considering these additive effects and the correlation between soil NO_3-N and soil moisture, was fitted to this dataset and validated by the field data of 1999. It is concluded that this model may be applicable to predict soil NO_3-N level and soil moisture.

KEYWORDS: non-point source pollution, NO_3-N, precision agriculture, exploratory data analysis, MANOVA, multivariate statistical analysis

INTRODUCTION

Nitrogen required by crops comes from soil, biological fixation from atmospheric nitrogen, and N fertilizers (Sander et al., 1994). Besides a measure of potential N availability, soil NO_3-N content may be a risk index of nonpoint pollution to the environment. Nitrogen creates an environmental problem because nitrogen compounds can be transported in surface runoff and nitrate can be leached into groundwater (CAST, 1991; Lykins et al., 1994). In the past decades, driven by public concern about pollution of ground and surface waters, many studies have been conducted to improve N fertilizer efficiency (Sander et al., 1994). Generally, soil testing is used to determine the residual NO_3-N in the root zone and to recommend optimal N fertilizer rates (Sander et al., 1994).

The soil NO_3-N content may be affected by various factors. Compared with the very slow processes of soil N mineralization and nitrification, application of N fertilizer may drastically change the soil NO_3-N level (Gentry et al., 1998). Fertilizer N may be adsorbed by microorganisms before the crop root system is sufficiently developed to compete with microbial uptake of inorganic N, and incorporated by soil microbes into their biomass, temporarily immobilizing it until carbon, regulated by soil moisture, becomes limiting (Gentry et al., 1998). Agriculture cultural practices also closely affect soil NO_3-N level. Gentry et al. (1998) found that crop rotation, fertilizer type, and fertilizer application timing resulted in varied soil inorganic N pools. Sander et al. (1994) made use of the relationship between inorganic N pools and cultural practices to recommend optimal nitrogen management. Related to NO_3^- leaching and N uptake, climate, especially precipitation, may affect soil NO_3-N content. Drury et al. (1996) found that the greatest loss of NO_3^- in tile drainage occurred after a dry growing season, which limited maize yields and N uptake.

Taking the three-year data measured in a 25-ha field located near Ames, Iowa, and employing multivariate statistical analysis techniques, this paper explored the intricate relationships among soil NO_3-N level and its predominant affecting factors, including fertilizer application rate, soil, climate, and cultural practices.

MATERIALS AND METHODS

The chosen area for the study is the Larson Field, a 25-ha row-crop field located near Ames, Iowa. As with most agricultural fields of the Midwest, it has a corn-soybean rotation. In this field, corn, soybean, and corn were planted in 1996,1997,and 1998 respectively. For each of the three years, the Larson Field was divided into several strips treated with N fertilizer of low, medium, and high rates. In 1996, 1997, and 1998, 40, 9, and 9 points were randomly selected respectively to measure soil NO_3-N content and soil moisture at eight depths or sublayers (sublayers 1—8) of 0 to 6 cm, 6 to 12 cm, 12 to 18 cm, 18 to 24 cm, 24 to 30 cm, 30 to 36 cm, 36 to 42 cm, and 42 to 48 cm. For each of the combinations of locations and depths, several soil samples were randomly taken and analyzed. Moreover, a rainfall gauging stations was set up to record the precipitations. According to the records and long-history statistical analysis of precipitations in Ames, 1996, 1998,and 1997 can be categorized as dry, normal, and wet year respectively. Taken N fertilizer application rate, soil depth, and year as three categorical factors, a three-way contingency table can be formed for the measured soil NO_3-N content and soil moisture data (not shown due to large size). The soil depth will reflect soil properties varied vertically, and year will comprehensively represent the climate situations and the cultural practices. However, in 1998, 26 NO_3-N contents were randomly missed, resulting in an incomplete dataset.

To avoid losing data information, the EM algorithm was employed to impute the missing values and to create a complete dataset. The EM algorithm is a general technique for fitting models to incomplete data (Johnson et al., 1999). It capitalizes on the relationship between missing data and the unknown parameters of a data model. If we knew the missing values, then estimating the model parameters would be straightforward. Similarly, if we knew the parameters of the data model, then it would be possible to obtain unbiased predictions for the missing values (Rubin, 1978). This interdependence between model parameters and missing values suggests an iterative method where we first predict the missing values based on assumed values for the parameters, use these predictions to update the parameters estimates, and repeat (Dempster et al., 1997). The sequence of parameters converges over the distribution of the missing values (Little et al., 1987; Schafer, 1997). An EM macro, written in the SAS IML (SAS Institute Inc., 1996), was used to impute the missing NO_3-N contents. With the convergence criterion of 0.00001, only 4 iterations were needed to complete the imputation.

Using the imputed complete dataset, the sample mean plots were employed to visually identify the main effects of and the interactions among these three factors. Furthermore, a three-way MANOVA model was employed to test the findings from these plots (Johnson et al., 1999). Defining N fertilizer application rate as factor 1, soil depth as factor 2, and year as factor 3, the MANOVA model can be written as:

$$\begin{cases} \underline{y}_{ijkl} = \underline{\mu} + \underline{\tau}_i + \underline{\beta}_j + \underline{\gamma}_k + (\underline{\tau\beta})_{ij} + (\underline{\tau\gamma})_{ik} + (\underline{\beta\gamma})_{jk} + (\underline{\tau\beta\gamma})_{ijk} + \underline{\varepsilon}_{ijkl} \\ \sum_{i=1}^{3} \underline{\tau}_i = \sum_{j=1}^{8} \underline{\beta}_j = \sum_{k=1}^{3} \underline{\gamma}_k = \sum_{i=1}^{3} (\underline{\tau\beta})_{ij} = \sum_{i=1}^{3} (\underline{\tau\gamma})_{ik} = \sum_{j=1}^{8} (\underline{\tau\beta})_{ij} = \sum_{k=1}^{3} (\underline{\tau\gamma})_{ik} = \sum_{j=1}^{8} (\underline{\beta\gamma})_{jk} = \sum_{k=1}^{3} (\underline{\beta\gamma})_{jk} = \sum_{i=1}^{3} (\underline{\tau\beta\gamma})_{ijk} = \sum_{j=1}^{8} (\underline{\tau\beta\gamma})_{ijk} = \sum_{k=1}^{3} (\underline{\tau\beta\gamma})_{ijk} \\ i = 1,2,3 \\ j = 1,2,3,\cdots,8 \\ k = 1,2,3 \\ l = 1,2,\cdots,n_{ijk} \end{cases} \quad (1)$$

where, n_{ijk} -- the sample size at ith level of factor 1, jth level of factor 2, and kth level of factor 3;

$\underline{y}_{ijkl}$ -- the lth measurement vector (2×1) at ith level of factor 1, jth level of factor 2, and kth levelof factor 3;

$\underline{\mu}$ -- overall level vector(2×1);

$\underline{\tau}_i$ -- main effect vector (2×1) of factor 1;

$\underline{\beta}_j$ -- main effect vector (2×1) of factor 2;
$\underline{\gamma}_k$ -- main effect vector (2×1) of factor 3;
$\underline{(\tau\beta)}_{ij}$ -- interaction vector (2×1) between factor 1 and factor 2;
$\underline{(\tau\gamma)}_{ik}$ -- interaction vector (2×1) between factor 1 and factor 3;
$\underline{(\beta\gamma)}_{jk}$ -- interaction vector (2×1) between factor 2 and factor 3;
$\underline{(\tau\beta\gamma)}_{ijk}$ -- interaction vector (2×1) among the three factors;
$\underline{\varepsilon}_{ijkl}$ -- random error vector (2×1).

Generally, model (1) assumes that $\underline{\varepsilon}_{ijkl}$ has independent bivariate normal distribution with a common covariance matrix reflecting the correlation between soil NO_3-N content and soil moisture.

Based on above analyses, a multivariate linear regression model was fitted to the dataset and validated with field data measured in 1999.

RESULTS AND DISCUSSIONS

Inferring the Implications by the Sample Mean Plots

The sample means of soil NO_3-N content and soil moisture are plotted in Fig. 1 and 2 respectively. It can be seen that:

- In Fig. 1, the curves vary with soil depth, indicating that the main effects of soil depth are expected. The NO_3-N levels reach their peaks in the first or second sublayers regardless of N fertilizer application rate and year. Gentry et al. (1998) also found that inorganic N pool is closely related to soil depth.
- In each of the panels of Fig. 1, the three curves have different heights, indicating that the main effects of application rate are expected. However, the effects are inconsistent from year to year and depth to depth. For 1996 (dry year), the descending sequence of soil NO_3-N content in the sublayer 1 corresponds to the medium, low, and high application rate respectively, in the sublayers 2 – 5 to the low, medium, and high rate respectively, and in the sublayers 6 – 8 to the high, low, and medium rate

respectively. For 1997 (wet year), the descending sequence of soil NO_3-N content in the sublayers 1 –3 corresponds to the high, low, and medium application rate respectively, and in the other sublayers to the high, medium, and low rate respectively. And for 1998 (normal year), the sequence in the sublayers 1, 2, 7, and 8 corresponds to the high, medium, and low application rate respectively, in the sublayers 3 to the high, low,and medium rate respectively, in the sublayers 4 and 5 to the low, medium,and high rate respectively, and in the sublayers 6 to the medium, low, and high rate respectively. Such intricate interweaving between the positive and negative effects of N fertilizer application rate may result in insignificant interactions among these three factors, and between application rate and soil depth and year. As indicated in Fig. 1, the curves corresponding to the sublayers with consistent application-rate effects are almost parallel, implying that application rate and soil depth may not interact. Furthermore, in each of the panels (a),(c), and (c), for each of the sublayers, the absolute differences between the heights of the two curves corresponding to the different application rates are almost equal, implying that insignificant interaction between application rate and year is expected. Finally, across (a), (b), and (c), the three curves corresponding to the same application rates are almost parallel, indicating that the three factors may not interact.

- However, the three curves corresponding to the same application rates across (a), (b), and (c) in Fig. 1 have different heights, implying that the main effects of year are expected.

- In Fig. 2, the curves vary with soil depth. Thus, the main effects of soil depth on soil moisture are expected. The general trend is that the lower sublayers have lower soil moisture. However, for 1997 and 1998,the second sublayer had higher soil moisture than the first sublayer due to that crops uptook much water from the first sublayer.
- In Fig. 2, for each of the panels (a), (b), and (c), the three curves have different heights, implying that application rate has effect on soil moisture. Except for the sublayer 1 in 1998, the descending sequence of soil moisture in sublayers 1 – 5 corresponds to the high, medium, and low application rate respectively. The high application rate prompted crop growth and increased crop root system (Jaynes et al., 1999). The enriched roots may keep soil moisture. For the other sublayers, application rate has either positive or negative effects on soil moisture. As with soil NO_3-N content, there may not be interaction effects on soil moisture among these three factors, and between application rate and soil depth and year, due to the interweaving of the positive and negative effects. In each of the panels, the three curves corresponding to the sublayers with consistent application-rate effect are almost parallel, implying that insignificant interaction between application rate and soil depth is expected, and the absolute differences between the heights of the two curves corresponding to the different application rates are almost equal across (a), (b),and (c), implying that insignificant interaction between application rate and year is expected. Finally, across (a), (b), and (c), the three curves corresponding to the same application rates are almost parallel, indicating that the three factors may not interact.

- However, the three curves corresponding to the same application rates across (a), (b), and (c) in Fig. 2 have different heights, implying that the main effects of year on soil moisture are expected.

Inferring the Implications by the MANOVA Model

While the inferences made by the above sample mean plots provided much information about the main effects of and interactions between the factors, they are qualitative analyses and don't consider the correlation between soil NO_3-N content and soil moisture. Therefore, the MANOVA model (1) was employed to further quantitatively explore the implications of soil NO_3-N level. Table 1 summarizes the SAS (SAS Institute Inc., 1996) outputs by fitting model (1) to the imputed complete dataset. At confidence level of 0.05, the main effects of the three factors are significant, but the two- and three-factor interactions are insignificant. The inferences of the MANOVA model are fully comparable with the sample mean plots. Moreover, the residual plots (Fig. 3) have no obvious pattern, and thus the model holds for this dataset.

Fitting a Multivariate Linear Regression Model

Both the sample mean plots and the MANOVA model (1) indicated that the main effects of the three factors are significant but they may not interact. Therefore, the effects of these factors are additive, and a multivariate linear regression model, which only includes the main effects, will be appropriate. Employing dummy variables, the regression model will be:

$$Y_{962\times 2} = X_{962\times 12}\beta_{12\times 2} + \varepsilon_{962\times 2} \tag{2}$$

where,

$$Y_{962\times12} = \begin{bmatrix} y_{1,1} & y_{1,2} \\ y_{2,1} & y_{2,2} \\ \cdots & \cdots \\ y_{962,1} & y_{962,2} \end{bmatrix}$$ ---- measurement matrix;

$$\beta_{12\times2} = \begin{bmatrix} \beta_{1,1} & \beta_{1,2} \\ \beta_{2,1} & \beta_{2,2} \\ \cdots & \cdots \\ \beta_{12,1} & \beta_{12,2} \end{bmatrix}$$ ---- regression coefficient matrix;

$$\varepsilon_{962\times12} = \begin{bmatrix} \varepsilon_{1,1} & \varepsilon_{1,2} \\ \varepsilon_{2,1} & \varepsilon_{2,2} \\ \cdots & \cdots \\ \varepsilon_{962,1} & \varepsilon_{962,2} \end{bmatrix}$$ ---- random error matrix. In general, it is assumed that the error has independent bivariate normal distribution, The normality assumption may be released for this dataset due to large sample size (Johnson et al., 1999).

$$X_{962\times12} = \begin{bmatrix} 1 & x_{1,1} & x_{1,2} & \cdots & x_{1,11} \\ 1 & x_{2,1} & x_{2,2} & \cdots & x_{2,11} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ 1 & x_{962,1} & x_{962,2} & \cdots & x_{962,11} \end{bmatrix}$$ -- design matrix defined by:

$$x_{i,1} = \begin{cases} 1 & \text{low application rate} \\ -1 & \text{high application rate} \\ 0 & \text{medium application rate} \end{cases}$$

$$x_{i,2} = \begin{cases} 1 & \text{medium aplication rate} \\ -1 & \text{high application rate} \\ 0 & \text{low application rate} \end{cases}$$

$$x_{i,3} = \begin{cases} 1 & 1996 \\ -1 & 1998 \\ 0 & 1997 \end{cases}$$

$$x_{i,4} = \begin{cases} 1 & 1997 \\ -1 & 1998 \\ 0 & 1996 \end{cases}$$

$$x_{i,5} = \begin{cases} 1 & \text{sublayer 1} \\ -1 & \text{sublayer 8} \\ 0 & \text{others} \end{cases}$$

$$x_{i,6} = \begin{cases} 1 & \text{sublayer 2} \\ -1 & \text{sublayer 8} \\ 0 & \text{others} \end{cases}$$

$$x_{i,7} = \begin{cases} 1 & \text{sublayer 3} \\ -1 & \text{sublayer 8} \\ 0 & \text{others} \end{cases}$$

$$x_{i,8} = \begin{cases} 1 & \text{sublayer 4} \\ -1 & \text{sublayer 8} \\ 0 & \text{others} \end{cases}$$

$$x_{i,9} = \begin{cases} 1 & \text{sublayer 5} \\ -1 & \text{sublayer 8} \\ 0 & \text{others} \end{cases}$$

$$x_{i,10} = \begin{cases} 1 & \text{sublayer 6} \\ -1 & \text{sublayer 8} \\ 0 & \text{others} \end{cases}$$

$$x_{i,11} = \begin{cases} 1 & \text{sublayer 7} \\ -1 & \text{sublayer 8} \\ 0 & \text{others} \end{cases}$$

where, $i = 1, 2, \cdots, 962$.

Using SAS GLM (SAS Institute Inc., 1996), the regression coefficient matrix and MANOVA test criteria can be gotten. The MANOVA test indicated that $x_{i,2}$ is insignificant at any confidence level (p-value =0.95), and thus term $x_{i,2}$ was dropped off when fitting the final regression model. The regression coefficient matrix will be:

$$\beta = \begin{bmatrix} 2.5292 & 0.1926 \\ 0.0612 & -0.0035 \\ --- & --- \\ 0.2900 & 0.0140 \\ -0.7548 & -0.0105 \\ 2.9650 & 0.0324 \\ 1.9204 & 0.0294 \\ -0.09859 & 0.0131 \\ -0.7498 & -0.0003 \\ -0.9241 & -0.0121 \\ -1.0743 & -0.0211 \\ -1.1238 & -0.0206 \end{bmatrix}$$

Table 2 gives the MANOVA test for the regression coefficients. It can be seen that all of the coefficients are significant at the model-selection confidence level of 0.15 (SAS Institute Inc., 1996). Furthermore, the residual plots (Fig. 4) have no obvious pattern and thus the regression model (2) holds for this dataset.

Validating the Fitted Regression Model

In April 2, 1999, 9 locations were randomly selected to measure the soil NO_3-N content and soil moisture of the Larson Field. Because no any fertilizer was applied before this date, low application rate was assumed while validating model (2). And according the rainfall record, 1999 was a normal year. Under these conditions, the predicted values of the soil NO_3-N content and soil moisture by model (2) were compared with the measured values (Fig. 5).

The determinate coefficients R^2 of the soil NO_3-N content and soil moisture are 0.82 and 0.45 respectively. Therefore, the model is applicable for predicting soil NO_3-N content and soil moisture, and may predict soil NO_3-N content better than soil moisture.

CONCLUSIONS

Soil NO_3-N may benefit crop growth but is a potential non-point pollution source for water. Its content is comprehensively affected by various factors, including N fertilizer application rate, soil, and climate (especially precipitation). Understanding the interwoven relationship between soil NO_3-N content and these factors will undoubtedly be helpful to improve N fertilizer efficiency and to reduce water pollution risk, and thus will prompt the practices of precision agriculture. The exploratory analyses of the field data obtained from 1996 to 1998 indicated that the effects of N fertilizer application rate, soil depth, and year on the soil NO_3-N content may be additive. The Statistical MANOVA model further verified this result. Therefore, a multivariate linear regression model, considering the main effects of N fertilizer application rate, soil depth, and year, and the correlation between soil NO_3-N content and soil moisture, is appropriate for this dataset. The validation by 1999 field data indicated that the regression model may be applicable to predict soil NO_3-N level and soil moisture, and that soil NO_3-N can be predicted more accurately than soil moisture.

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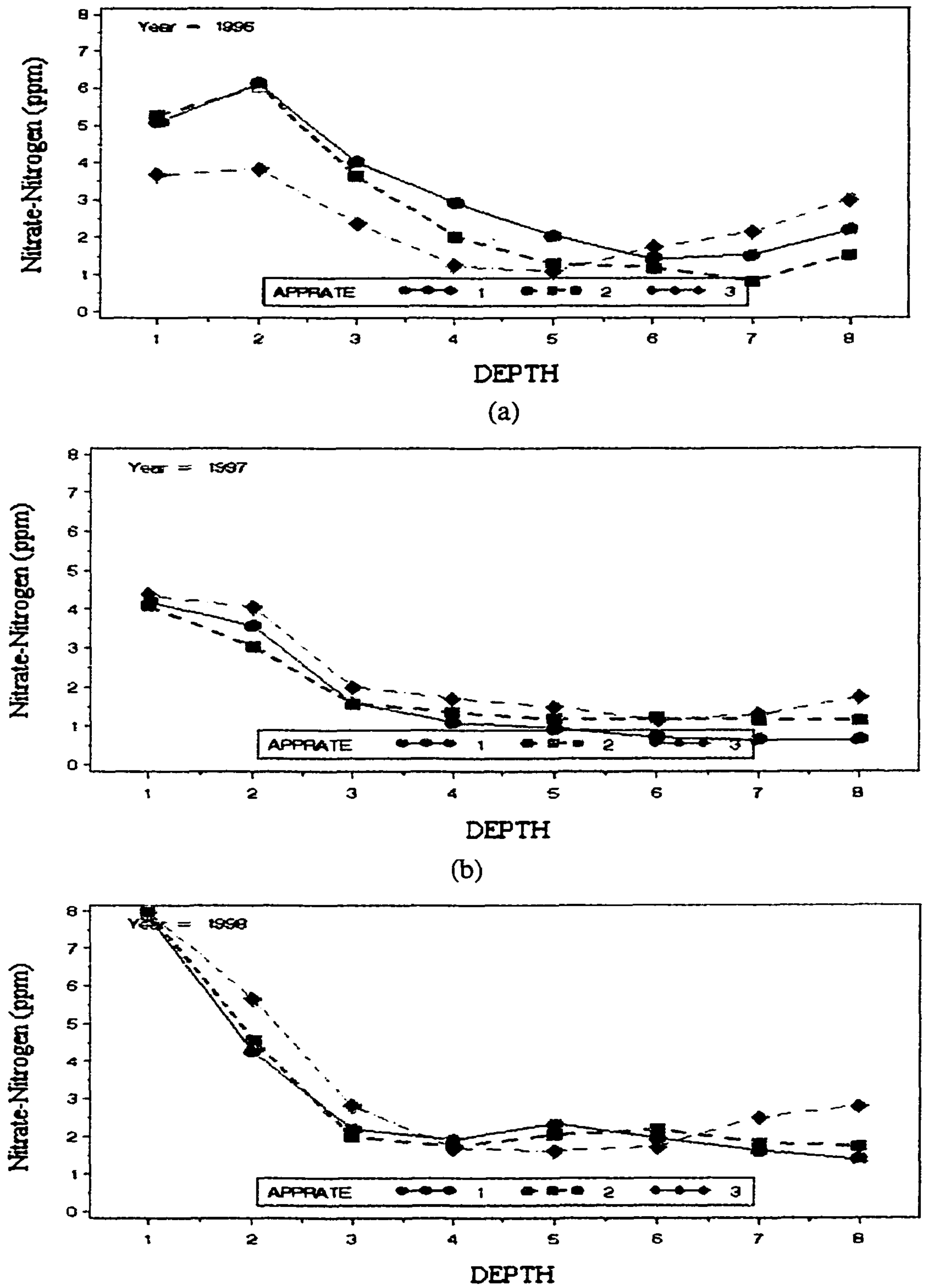
Table 1 Test Criteria and F Approximations for the MANOVA Model (1)

Effects & Interactions†	Wilks' Lambda	F	df_1 (numerator degree freedom)	df_2 (denominator degree freedom)	P>F*
Apprate	0.9867	2.9736	4	1776	0.0184*
Year	0.8324	42.6460	4	1776	0.0001*
Depth	0.5173	49.5152	14	1776	0.0001*
Apprate*Year	0.9898	1.1438	8	1776	0.3304
Apprate*Depth	0.9834	0.5334	28	1776	0.9786
Year*Depth	0.9687	1.0164	28	1776	0.4413
Apprate*Year*Depth	0.9758	0.3909	56	1776	1.0000

Note: † Apprate: N fertilizer application rate; Year: study years; Depth: soil depth;
* *: significant at confidence level of 0.05.

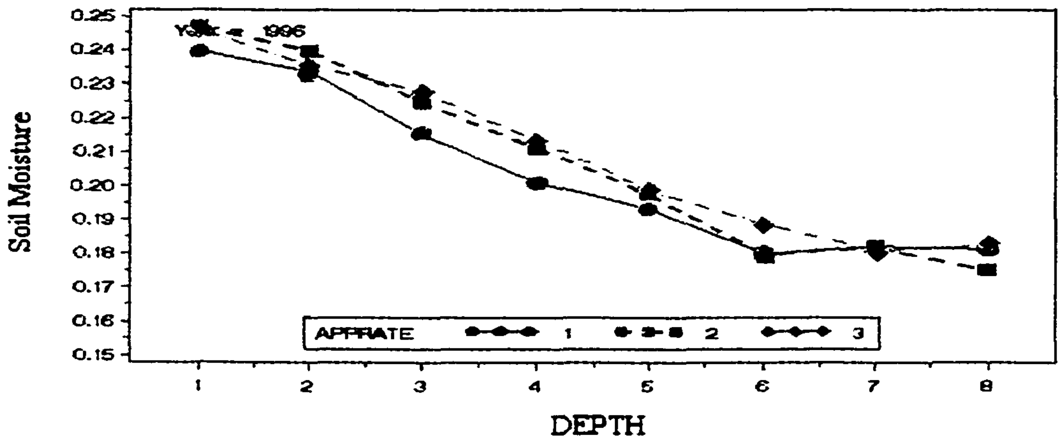
Table 2 Test Criteria and F Approximations for the Regression Coefficient Matrix

Coefficient	Wilks' Lambda	F	df_1 (numerator degree freedom)	df_2 (denominator degree freedom)	P>F
$[\beta_{1,1}, \beta_{1,2}]$	0.01580	29549.47	2	949	0.0001
$[\beta_{2,1}, \beta_{2,2}]$	0.9858	6.8305	2	949	0.0011
$[\beta_{3,1}, \beta_{3,2}]$	—	—	—	—	—
$[\beta_{4,1}, \beta_{4,2}]$	0.8361	93.0129	2	949	0.0001
$[\beta_{5,1}, \beta_{5,2}]$	0.8726	69.2856	2	949	0.0001
$[\beta_{6,1}, \beta_{6,2}]$	0.6997	203.6617	2	949	0.0001
$[\beta_{7,1}, \beta_{7,2}]$	0.7671	144.0318	2	949	0.0001
$[\beta_{8,1}, \beta_{8,2}]$	0.9514	24.2420	2	949	0.0001
$[\beta_{9,1}, \beta_{9,2}]$	0.9918	3.9132	2	949	0.0203
$[\beta_{10,1}, \beta_{10,2}]$	0.9480	26.0136	2	949	0.0001
$[\beta_{11,1}, \beta_{11,2}]$	0.8727	69.0241	2	949	0.0001
$[\beta_{12,1}, \beta_{12,2}]$	0.8762	67.0258	2	949	0.0001

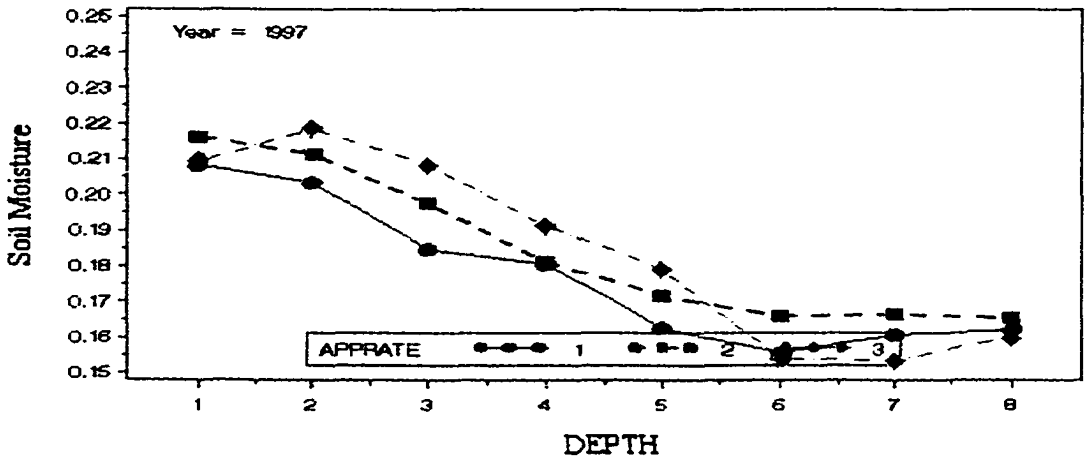


(c)

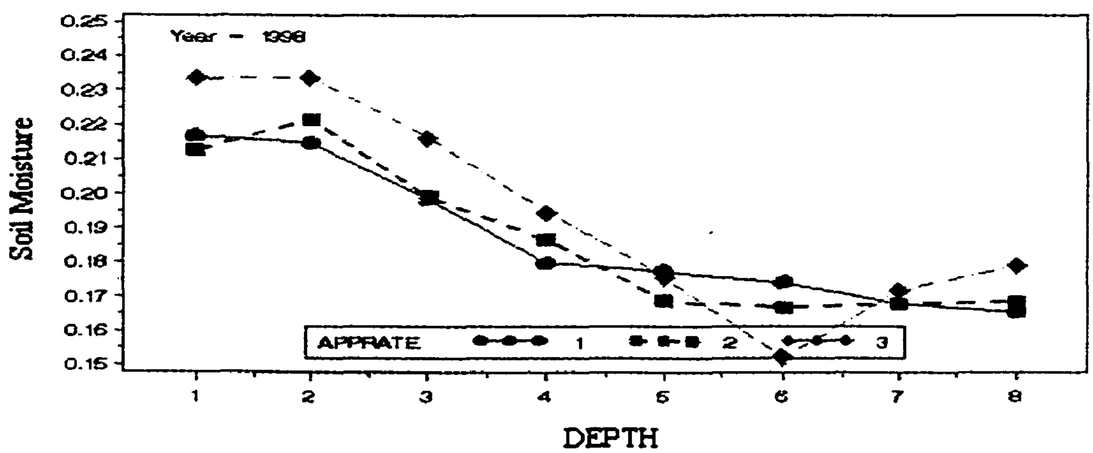
Fig. 1 Sample Mean Plots for Soil NO_3-N Content
(DEPTH: soil depth, cm; APPRATE: application rate)



(a)

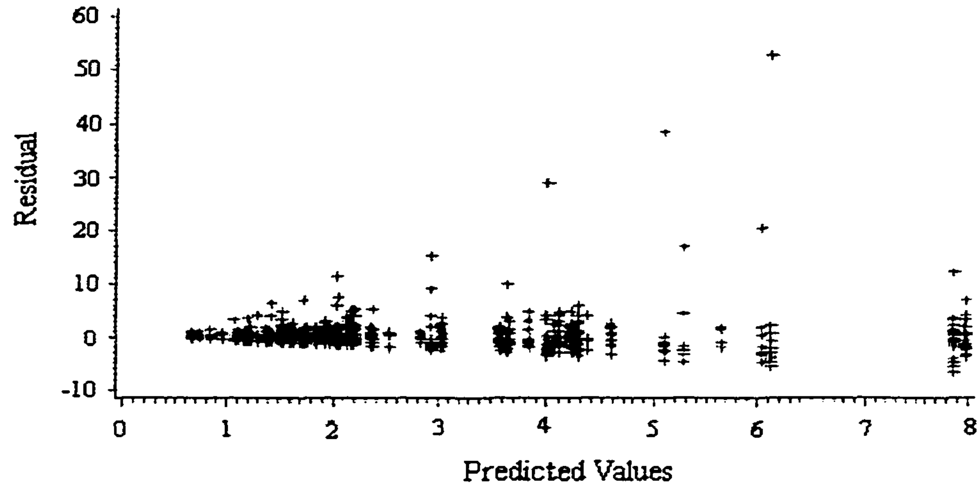


(b)

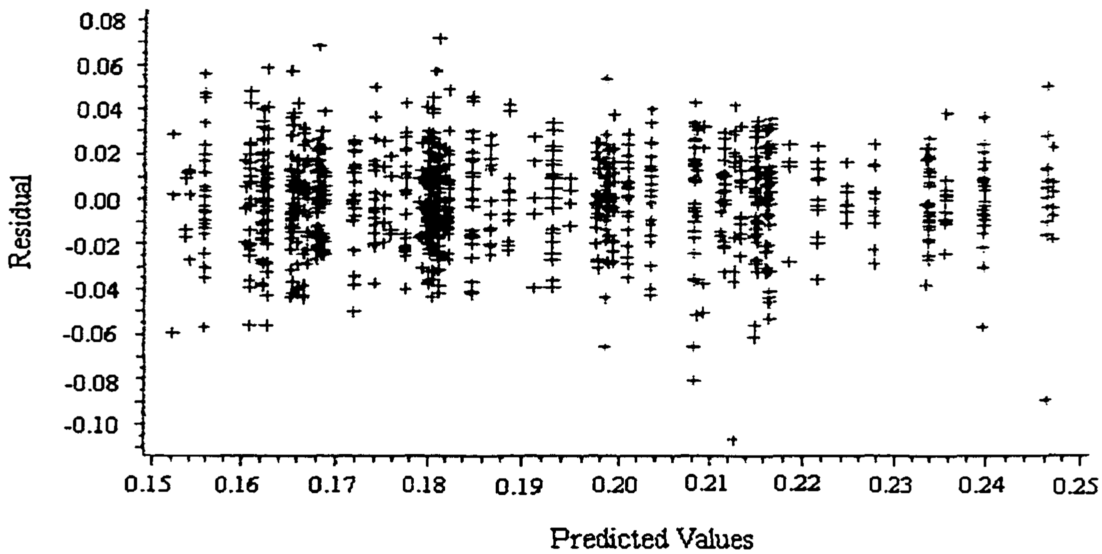


(c)

Fig. 2 Sample Mean Plots for Soil Moisture
(DEPTH: soil depth, cm; APPRATE: application rate)

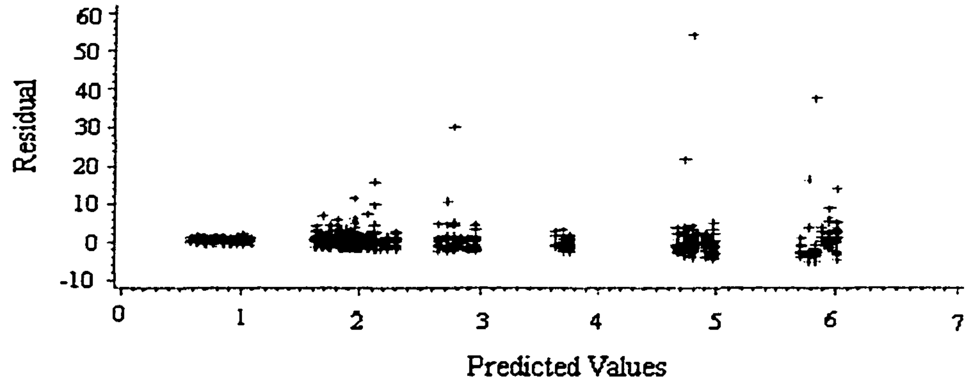


(a) soil NO_3-N content

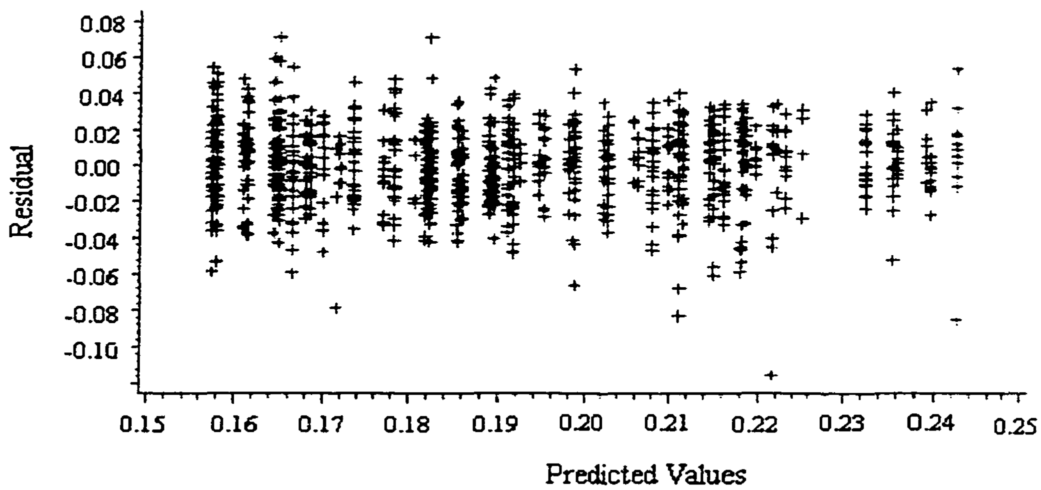


(b) soil moisture

Fig. 3 Residual Plots of the MANOVA Model (1)

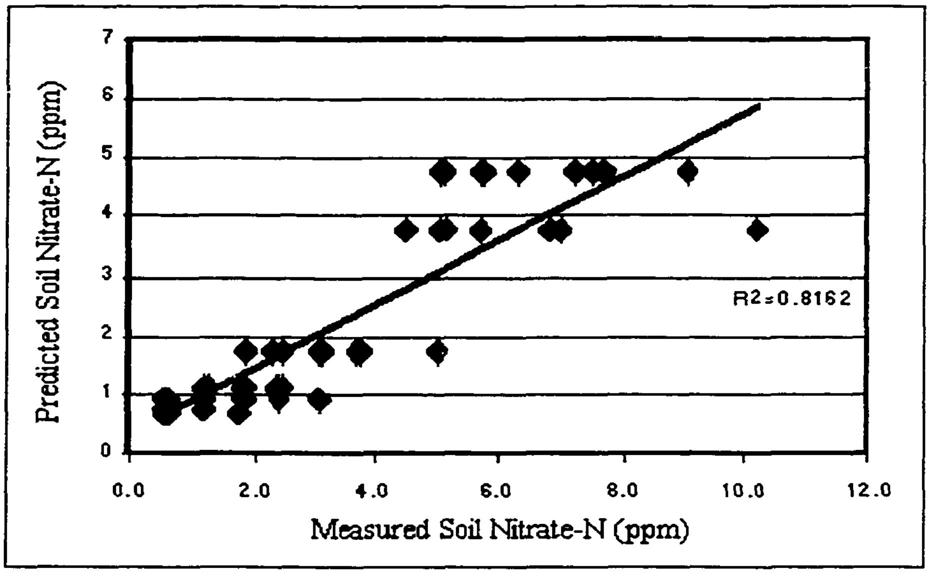


(a) soil NO_3-N content

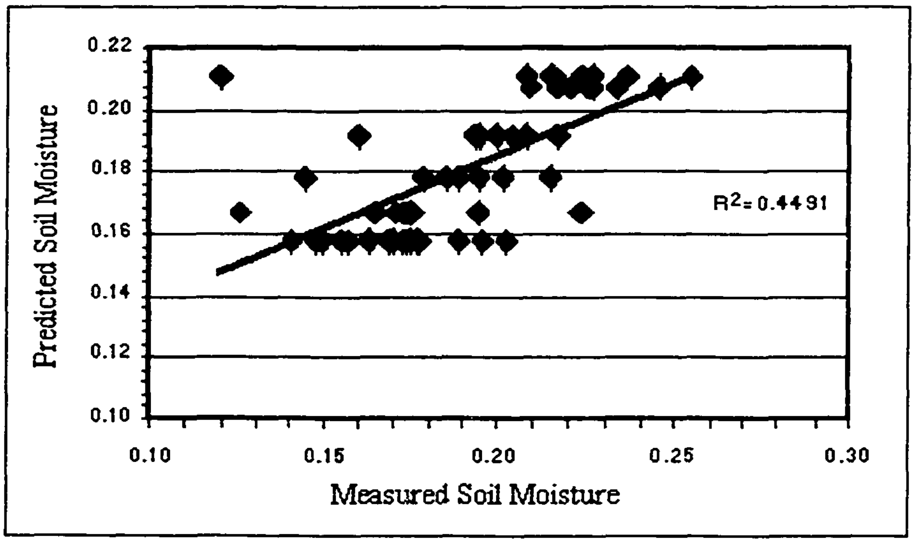


(b) soil moisture

Fig. 4 Residual Plots of the Regression Model (2)



(a) soil NO_3-N content



(b) soil moisture

Fig. 5 Predicted Values by Model (2) vs. the Measured Values in 1999

CHAPTER 5
DECISION TOOLS FOR EVALUATING ECONOMIC/ECOLOGIC RISKS OF PRECISION AGRICULTURE

A paper to be submitted to the Agricultural Systems

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ABSTRACT: The successful transfer of precision farming needs tools for evaluating the economic and environmental risks of precision agriculture. This paper presented such kind of GIS-based tools. Using these tools, the decision maker may do various what-if analyses from the arbitrary management practice to the practice simulated by the comprehensive GIS-based biophysical models such as GIS-based RZWQM. A 25-ha field located in the Central Iowa was employed to demonstrate the use of the tools.

KEYWORDS: Cost-benefit analysis, GIS, nitrogen decision, environment

Introduction

Precision farming is a developing technology to increase efficiency in the management of agriculture (Emmott et al., 1997). It may have two-fold benefits of reducing both the cost of producing the crop and the risk of environmental pollution from agrochemicals applied at levels greater than those required by the crop (Earl et al., 1996). While many researches have been conducted to improve the two core factors in precision farming, i.e., the measurement and the management of variability (Blackmore, 1994; Kowalski et al., 1996; Parkin and Blackmore, 1995; Auernhammer and Muhr, 1991; Larscheid and Blackmore, 1996; Schnug et al., 1994; Panten et al., 1998; and Algerbo and Thylen, 1998), there have been few studies with the specific objective of evaluating the potential role of precision agriculture on environmental quality (Hatfield, 2000) and developing tools for economic analysis in a sense of grid-based cost accounting (Wagner, 2000). However, successful transfer of precision farming technology between systems ultimately depends on whether the additional costs over time as calculated in a cost-benefit analysis (Emmot et al., 1997). In order to improve economic efficiency, precision farming must ensure that the cost of application of variable inputs is exceeded by the additional revenue from the production and sale of the extra output and the environmental improvements. This paper developed GIS-based tools written in ArcView Avenue script for evaluating economic and environmental benefits of precision agriculture. The decision maker may use these tools to do the grid-based cost-benefit analysis based on the selected management practices and to define optimal nitrogen application rate and timing to minimize nitrogen leaching loss.

Economic Benefit Evaluation Tool

To run their farms on the principles of precision farming, farmers must be willing to invest in technology and services of data collection, data processing, and input application equipments. Data collection, just to mention a few, may include yield mapping, positioning system (DGPS), spectrometer to determine the nitrogen requirement of plants, and appliances to take soil samples and to determine weed pressure. Data processing needs both hardware and software. And input application equipments, depending on the automation level, may consist of computer-guided fertilizer spreader, computer-guided herbicide sprayer, and computer-guided seeder. On the other hand, there are the benefits of increasing yields, lowering the quantity of inputs, and protecting or improving environmental quality. The revenues of these benefits ought to cover the extra cost of investments. Wagner (2000) analyzed the reasons and potentials for the additional profit and the cost reduction lying in the different approaches of traditional farm management and of precision farming.

The evaluation tool requires inputs of maps reflecting spatial variability and of current prices and capital costs. The maps are yield map, nitrate-N loss map, N-fertilizer application map, and field soil texture map. The soil texture map reflects the soil spatial variability within the field and may be created by digitizing soil paper map. The N-fertilizer application map can be arbitrarily decided by the farming manager or created using the GIS-based Nitrogen Decision Aid described later. The yield map and nitrate-N loss map reflect the agronomic and environmental variability across the field respectively resulted from the selected management practice identified by the N-fertilizer application map. These two maps may be produced using the simulation results from the GIS-based water quality and crop models such as the Root Zone Water Quality Model (RZWQM) and CERES. As a simple approximation, a historic yield map created by a harvest combine and nitrate-N losses sampled across the field may be used. In addition to the maps, the decision maker has to input the current prices of grain and N-fertilizer, capital costs of DGPS licence, software and fertilizer kit, and environmental penalty. The current prices vary crop by crop and year by year, and may be available from e-markets such as http: //www.e-markets.com and literatures (Snyder et al., 1998; DeBoer, 1998; Bongiovanni and Deboer, 1998; and Watkins et al., 1998). The prices can also be posted by the Australia's Business Review Weekly and and the USDA Economic and Statistics System (http: //jan.mannlib.cornell.edu/ess_entry.html), which includes weekly- or daily-updated capital costs of agriculture instruments and equipments as well. However, the subjective-dominated environmental penalty is mostly difficult to be defined. To the authors' knowledge, there is currently no accurate quantitative method to define this factor. In general, the penalty fee is positively related to the damages possibly caused by the environmental deterioration. The currently-used procedure is that the penalty is proposed by the U.S. Environmental Protection Agency (U.S. EPA) and judged by judgers. For example, U.S. EPA proposed a $128,920 environmental penalty to a San Antonio landlord who is in violation of the Residential Lead-Based Paint Hazard Reduction (American City Business Journal Inc., 2000).

The average yield is computed in terms of the inputted yield map. It is treated as the yield under traditional uniform management practice (Earl et al., 1997). From the model relating crop yield and applied N-fertilizer (Sander et al., 1994; Olness et al., 1998) for the whole field, the uniform N-fertilizer rate corresponding the average yield can be estimated. Assuming that the relationships between yield and applied N-fertilizer and between nitrate-N loss and applied N-fertilizer are only affected by the soil type, the yield map and nitrate-N loss map under the traditional uniform management practice may be derived from the relationships for each of the soils. The yield increases and nitrate-N loss changes may be estimated by comparing the maps under the traditional uniform management practice and the corresponding ones under precision farming management practice. A negative environment penalty will be added when the estimated nitrate-N loss decreases under precision farming management practice, but otherwise a positive penalty added. The cost-benefit is analyzed by summing up the benefits and costs of precision farming practice relevant to the averaged condition or traditional uniform management practice.

Figure 1 shows the ArcView GIS-based graphic user interface (GUI) of this evaluation tool. The GUI was developed in ArcView Avenue script, an object-oriented programming language. Through this GUI, the decision maker specifies the required maps, including yield map, nitrate-N loss map, N-fertilizer application map and soil texture map, and inputs the current prices, capital costs and environmental penalty fee. The economic evaluation is implemented by clicking the Do Analysis button. In addition to the cost-benefit analysis table shown at the right-bottom corner of the dialogue box, the maps showing the differences of yield and nitrate-N loss between under the traditional uniform management practice and under the precision farming management practice will be automatically created. The dialogue box also shows the grid information such as grid size and grid number in the Cells textbox, next to which map unit is displayed. The decision maker can interrupt the evaluation process at any time by clicking the Cancel button.

GIS-based Nitrogen Decision Aid

Each year, more than 10 billon kg of nitrogen fertilizer are applied to croplands in the United States at a cost of more than $3.5 billion (USDA Economics and Statistics System, 1998). It is estimated that the efficiency of this applied nitrogen ranges from about 20% to about 60% (Rennie et al., 1993). Thus, large amounts of fertilizer nitrogen are lost or wasted each year. It is possible to reduce this waste by applying just enough N-fertilizer to reach the critical soil nitrate concentration (Olness et al., 2000). Olness rt al. (1997), Cordes et al. (1997), and Sweeney et al. (1997) discussed the theory and development of nitrogen fertilizer decision aid to improve the efficiency.

A Nitrogen Decision Aid, developed by the North Central Soil Conservation Research Laboratory, Morris, MN, is a computerized program that predicts the amount of nitrogen mineralized from planting to side-dress or 5-leaf growth stage. The resulting output from the Nitrogen Decision Aid may be used as a guide to assist the user in making nitrogen management decisions. The detailed descriptions on the Nitrogen Decision Aid can be found at http: //www.mrsars.usda.gov/morris/products/author.htm.

Unfortunately, the Nitrogen Decision Aid can not effectively consider soil variability with field. A GIS-based Nitrogen Decision Aid, coupling ArcView GIS and this decision aid, was developed in this paper to enable the soil variability to be included in the nitrogen decision process. Figure 2 shows its GUI written in ArcView Avenue script. Using this interface, the user may define the field and the intended management practice by specifying soil map, soil sampling map and management map, define the weather condition by selecting a weather file, create input files automatically required by the Nitrogen Decision Aid, and generate the nitrogen application map.

The soil polygon map may be gotten from a data provider or digitized from a soil paper map. It is stored as either an ArcView shape file or Arc/Info coverage. The soil map defines soil spatial variability of the field and provides information on soil type, sand percentage, clay percentage, and organic matter content.

The soil sampling map is a point theme stored as either an ArcView shape file or Arc/Info coverage. It may be generated from a text file with geo-referenced information by clicking the Create the Soil Sampling Map from a Text File... button. The map provides the parameters measured at each of the sampling points, including sampling date, soil type of the sample, PH value, soil water content, and soil nitrate-N content of the 6-in thick soil profiles from ground surface to 24-in depth.

Like the soil polygon map, the management map is a polygon theme stored as either an ArcView shape file or Arc/Info coverage. It may be generated from the soil polygon map and a text file with management information corresponding to each of the soils by clicking the

Create the Management Map from a Text File... button. It provides the management information for the soils, including tillage method, sufficient nitrate level, planting date, and fertilizer application date and rate as elemental N.

The input files required by the Nitrogen Decision Aid will be automatically created by clicking the Make Input Files for the Decision Aid button. The files are named by the soil names with nit suffix and displayed in the right-upper list box (see Figure 2). The soil information will be extracted from the soil map, the soil sampling parameters from the soil sampling map, and the management information from the management map. For the soil where more than one points are sampled, the averages of the parameters measures at these points are taken to represent the parameters of the soil. Otherwise, the nearest neighborhood method is employed to estimate the parameters for the soil where there is no sampling point. Once the input files are generated, the user may click the Run the Nitrogen Decision Aid button to make nitrogen decision soil by soil and create a nitrogen application map by clicking the Create Application Map button. And the user may stop the decision process at any time by clicking the Cancel button.

Example Application

There are three options to use these tools to perform the what-if analyses on both the economic and ecologic risks of precision agriculture. First, the decision maker arbitrarily decides the nitrogen management practice and empirically estimates the possible yield and nitrate-N loss. The tools are employed to assess the economic benefits and environmental impacts. Second, the optional nitrogen management practice can be decided using the GIS-based Nitrogen Decision Aid. Both crop yields and nitrate-N losses under the selected nitrogen application map are empirically estimated. The tool for evaluating the economic benefits is used to do the cost-benefit analysis. Third, the nitrogen application map, optimally derived using the GIS-based Nitrogen Decision Aid, is fed into a GIS-based biophysical model such as GIS-based RZWQM to create the simulated yield and nitrate-N loss maps. And the economic benefits and environmental impacts are assessed using the tools.

This paper takes a 25-ha field located in the Central Iowa to demonstrate how the option 3 works. The field consists of four types of soils, Harps, Kossuth, Okoboji, and Ottosen. Before corn was planted on May 13, 1998, soils were sampled at nine points across the field to measure soil PH value, initial water content, and nitrate-N concentrations of the 24-in soil profile in 6-in interval. Using the GIS-based Nitrogen Decision Aid, the nitrogen application map was created as shown in Figure 3. It indicates that the Okoboji, Haps, Ottosen, and Kossuth soils should be treated by 100 kg/ha, 120kg/ha, 150kg/ha, and 172kg/ha N-fertilizer respectively to minimize nitrogen loss. This map was fed into the GIS-based RZWQM to get the simulated yield and nitrate-N loss maps. Taking the current prices and capital costs from the USDA Economics and Statistics System and arbitrarily assigning $1000.0/year environmental penalty fee, the cost-benefit analysis is conducted and shown in Figure 4. It can be seen that approximate $100,000 net benefits may be obtained under this management practice for this 25-ha field.

Conclusions

Precision farming may increase profit and reduce environmental pollution risk from agrochemicals. However, successful transfer of precision farming depends on that the extra output plus the environmental benefits exceed the extra investments. Currently, what is lacking is a tool for economic analysis in a sense of grid-based cost accounting and a tool for chemical application decision. This paper developed such tools for evaluating economic and ecologic risks of precision agriculture. These tools may be useful for both researchers and farming managers.

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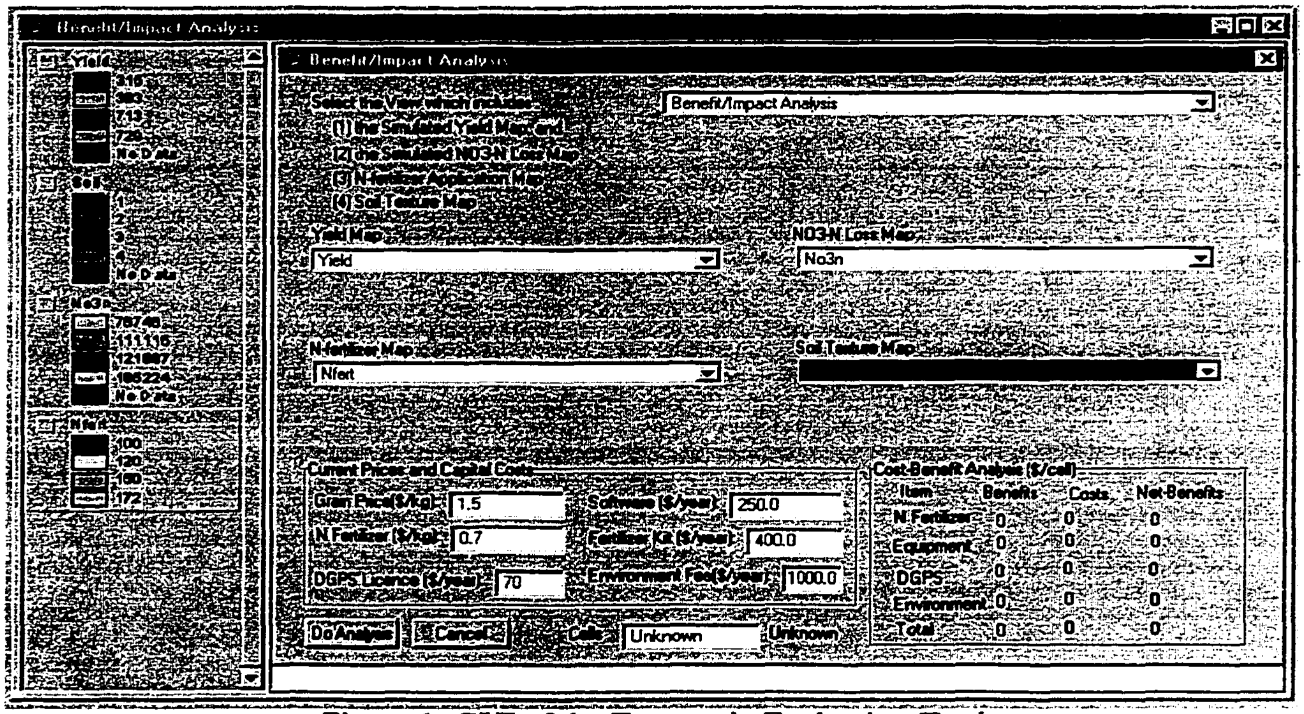


Figure 1 GUI of the Economic Evaluation Tool

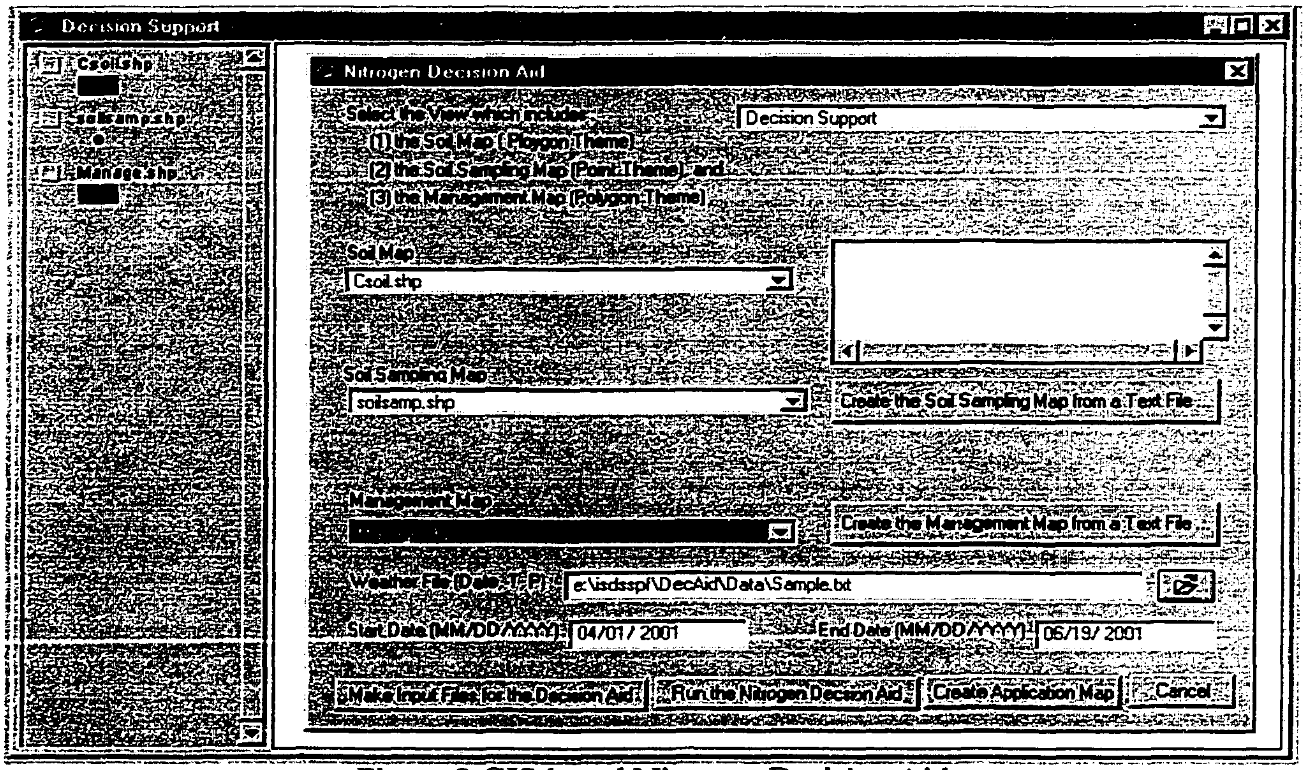


Figure 2 GIS-based Nitrogen Decision Aid

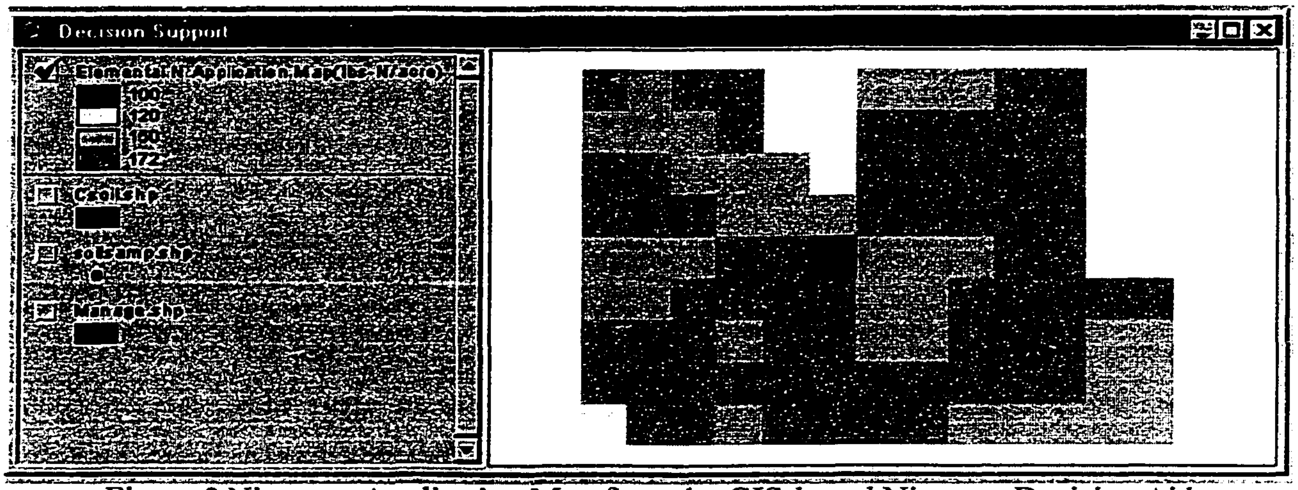


Figure 3 Nitrogen Application Map from the GIS-based Nitrogen Decision Aid

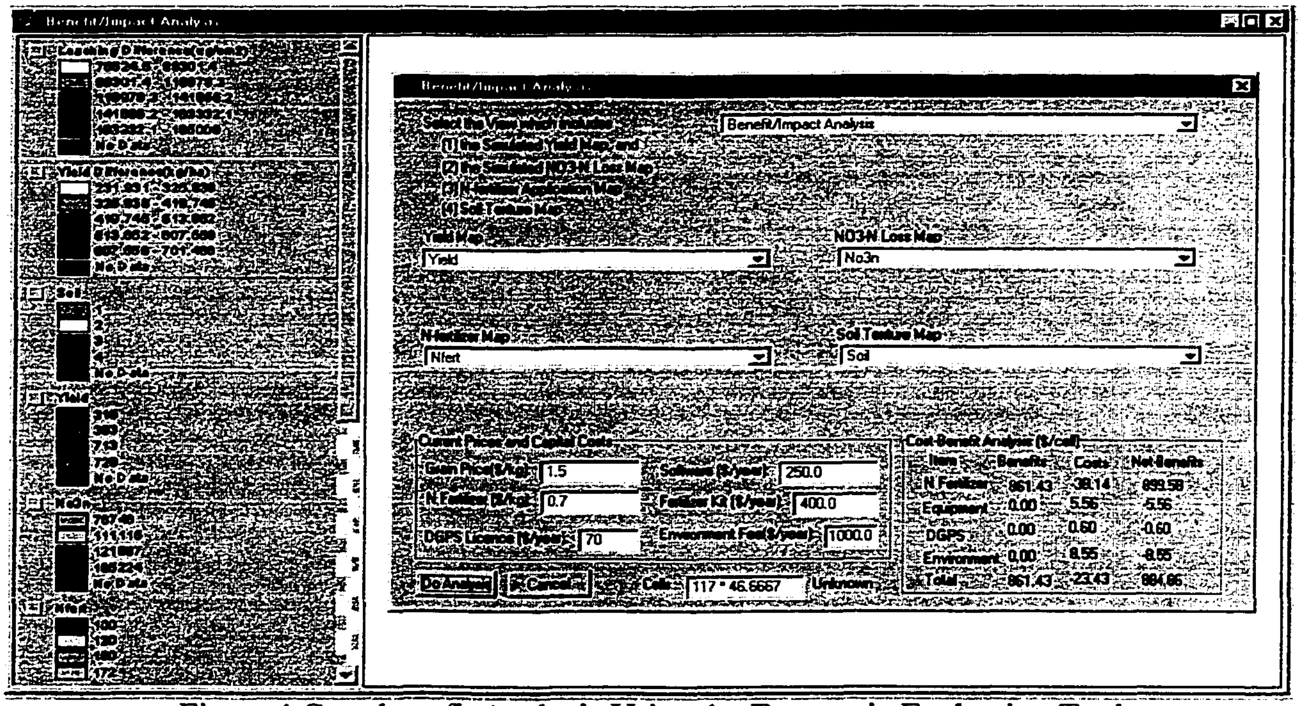


Figure 4 Cost-benefit Analysis Using the Economic Evaluation Tool

CHAPTER 6
USER'S MANUAL OF IDSSPA

IDSSPA includes modules for evaluating crop yield and chemical losses in response to site-specific management of agricultural inputs. Using this system, not only can users store, visualize, manipulate, and analyze spatial/non-spatial field experiment data, but they also can do various simulations through the easy-operated biophysical models, which take field spatial variability into account. In the system, the functionalities of the traditional models and analysis methods have been enhanced by coupling them with each other and with ArcView GIS. Uniquely desigened GIS-based interfaces enable the lumped biophysical models to incorporate and represent field spatial variability. Statistical and data mining tools are also included in the system to improve analysis of field measured data and to further enhance interpretation of model simulation results. Other components incorporated into the system are as follows: The CERES-Maize plant growth model seamlessly integrated with RZWQM to provide an alternative phonologically based model for predicting growth and yield of maize (corn), and several tools for evaluating economic and ecologic risks of precision agriculture implementation. The application examples indicated that IDSSPA is a useful research and decision make tool for precision agriculture at field and watershed scales.

6.1 IDSSPA Installation

6.1.1 Hardware and software requirements

The required hardware specifications are as follows:

CPU: Pentium II 300Mhz

Memory: 256 MB

Hard Drive Space: 1 GB

The required software specifications are as follows:

Operating System: Windows 95/98/NT/2000

Pre-installed software: ArcView GIS 3.1 or later

Spatial Analyst 1.1 extension or later

S-Plus 4.5 or later

S-Plus for ArcView 1.1 or later

6.1.2 Installation of IDSSPA

The program files have to be located under folder of ISDSSPF. The steps to install IDSSPA are:

- Place the CD in the CD-ROM drive
- Start Windows Explorer
- Drag the whole folder of ISDSSPF to the hard drive where you want to the system installed
- Right-click on the Desktop
- Choose New ⇒ Shortcut
- Navigate to ISDSSPF folder and select file pfdss.exe
- Click Next button, then Finish button

6.1.3 Loading IDSSPA

Once IDSSPA is installed, it can be loaded by double-clicking the system icon, namely pfdss.

When properly loaded, the logo of the IDSSPA should be shown as Figure 1. The users may access the websites of Iowa State University and of the Agricultural & Biosystems Engineering Department of Iowa State University by clicking the university and the department logos respectively. They also can start the IDSSPA or quit the system by clicking Continue and Cancel buttons respectively.

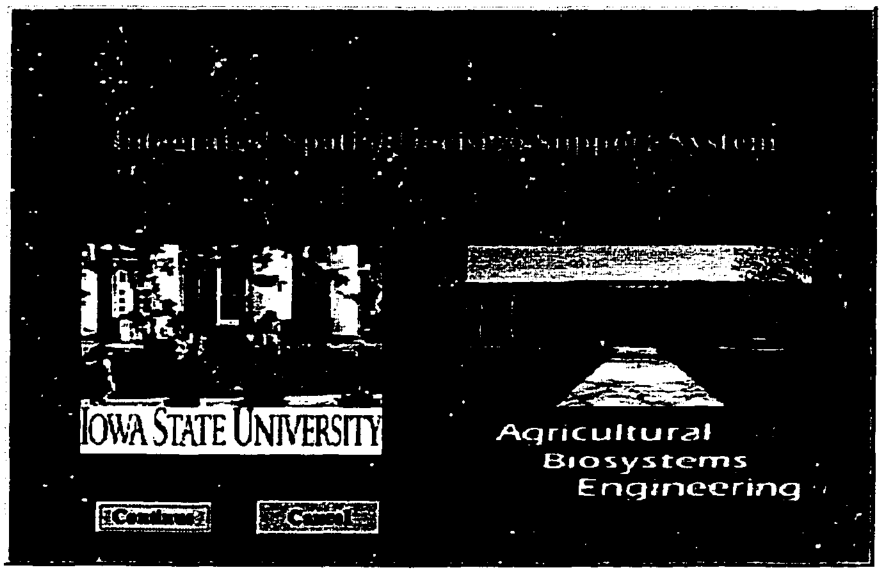


Figure 1 Logo of IDSSPA

6.2 Overview of IDSSPA

IDSSPA is a set of scripts developed using the Avenue and Visual Basic 6.0 programming languages. It runs on the ArcView GIS platform. Figure 2 shows the main user graphic user interface (GUI) of the IDSSPA. The buttons are standard ArcView functions. The menus of File, Edit, View, Theme, Analysis, Surface, and Graphics are provided by ArcView GIS and its extension of Spatial Analyst, and S-Plus and Spatial Statistics by S-Plus for ArcView GIS. The menus of the IDSSPA include Data, Prescription, Modeling, and Decision Support.

The Data menu is used to store and manipulate field topography, land use/land cover, soil sampling data, management options, and weather data, and will be discussed in detail in section 9.3. The Prescription menu is used to create lime, phosphors, and potassium spread maps according to the soil sampling data, and will be discussed in detail in section 9.4. The Modeling menu, the core of the system, is used to do the GIS-based crop modeling and the GIS-based water quality modeling, analyze data using S-Plus and spatial statistics functions, and evaluate economic benefits of precision agriculture. And the Decision Support menu is used to assist decision makers to evaluate ecologic risks of precision agriculture.

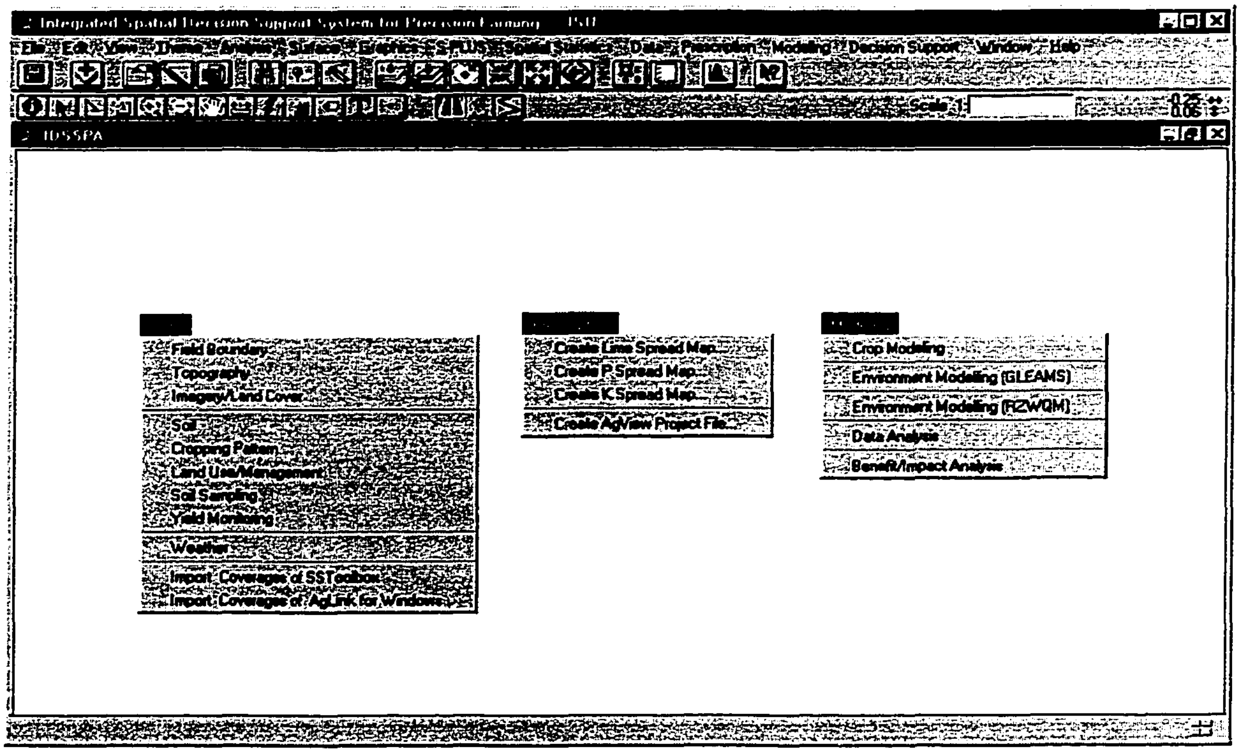


Figure 2 Main GUI of IDSSPA

6.3 Data Management Module

6.3.1 Store field geometric data

The Field Boundary, Topography, and Imagery/Land Cover include standard ArcView functions of on-screen digitizing and importing field DEM and land cover theme. The user may reference ArcView user's manual to learn how to do these.

6.3.2 Soil and crop yield data

Soil, Soil Sampling, and Yield Monitoring submenus take the soil polygon theme, soil sampling point theme, and yield point theme to rasterize the vector themes to the rater themes, which can be used for modeling and analysis. Three interpolation methods, including Kriging, Inverse Distance, and Spline, may be used to do the interpolation. Figure 3 shows how to manipulate soil texture data. The user needs to specify Output Grid Extent, Output Grid Cell Size by inputting Cell Size, Number of Rows, or Number of Cols. He/she also needs to select Interpolator method by checking Kriging or Others radio buttons. If the Kriging is checked, another dialogue shown in Figure 4 will ask users to select Z Value Field, choose Semi-variogram Model, and specify the Fixed Sample Count through the corresponding combobox or text box. Click Ok button to complete importing the soil texture data, or Cancel button to stop the importing process. When the Others are checked, the dialogues hown in Figure 5-6 allow users to select inverse distance interpolator (IDW) or spline interpolator (Spline) through the Method combobox, specify Z Value Field, and interpolator parameters. If the IDW is selected, the users need to check either Nearest Neighbors or Fixed Radius. The Nearest Neighbors needs parameters of No. of Neighbors, Power, and Barriers (Figure 5), whereas the Fixed

Radius needs parameters of Radius, Power, and Barriers (Figure 6). The Spline interpolator needs parameters of Weight, No. of Points, and Type (Figure 7).

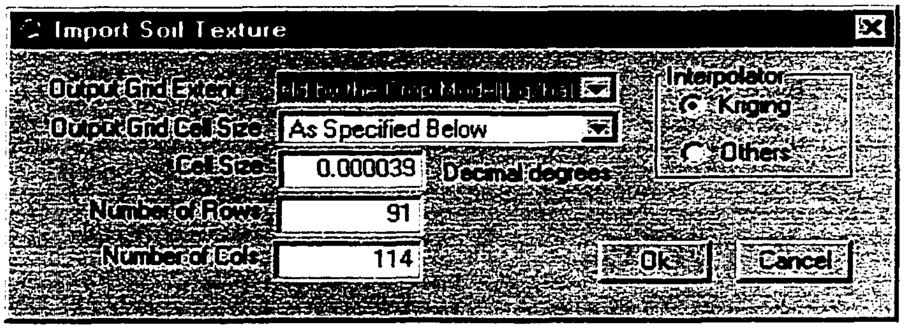


Figure 3 Main Dialog to Import Soil Texture

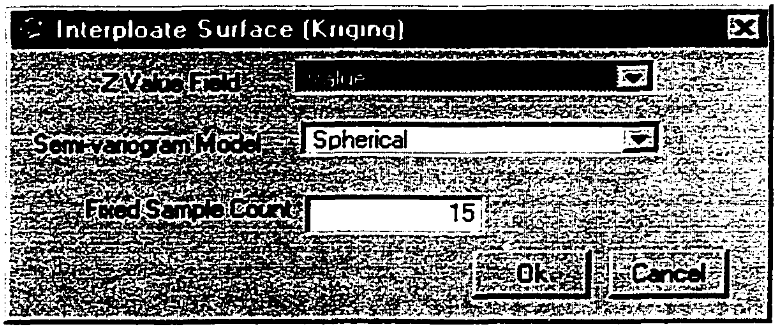


Figure 4 Dialogue to Specify Parameters of Kriging Interpolator

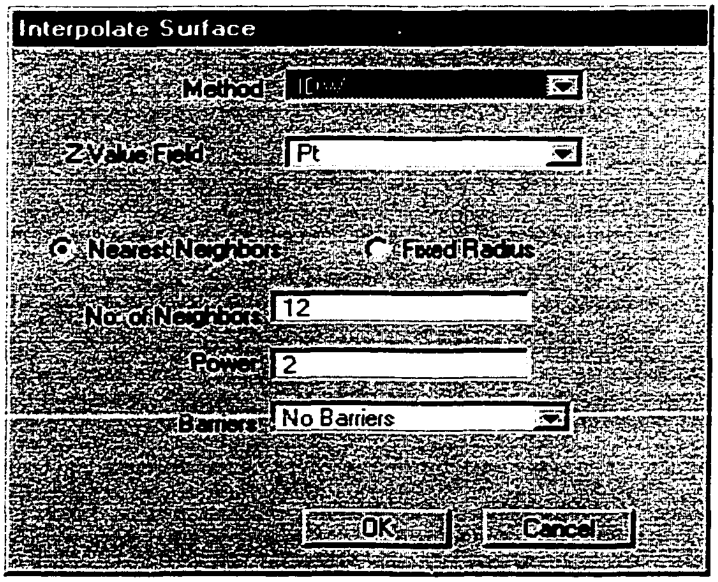


Figure 5 Parameters for IDW Using Nearest Neighbors

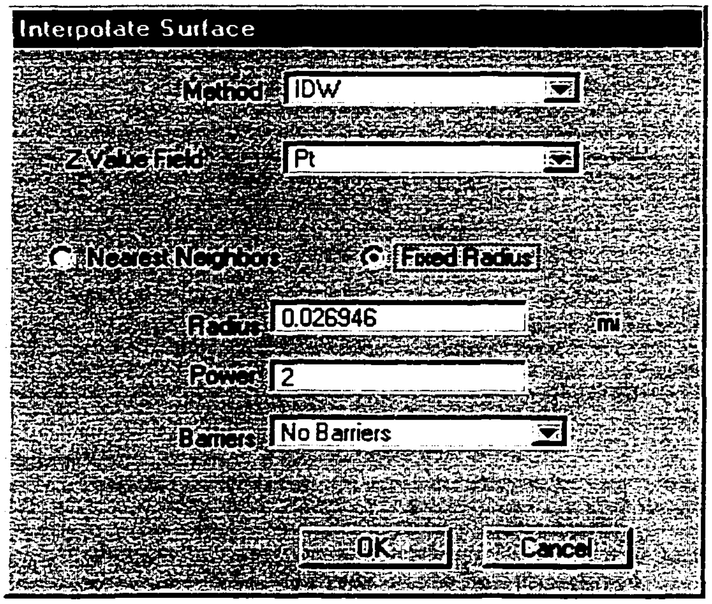


Figure 6 Parameters for IDW Using Fixed Radius

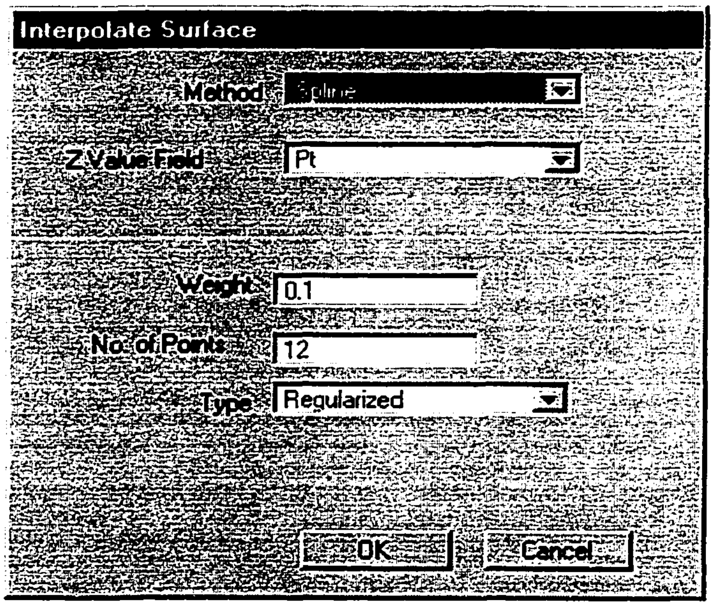


Figure 7 Parameters for Spline

The procedures to process soil sampling and yield point themes are exactly same as that of manipulating soil texture data. Thus, they are omitted here.

6.3.3 Management option data

The Cropping Pattern and Land Use/Management submenus use the standard function provided by a ArcView Extension, Edit Table values in Dialog. The users may reference ArcView User's Manual to learn how to use these two submenus.

6.3.4 Weather data

Through this submenu, the users may generate weather data and covert the generated weather data to the formats, which can be used by the CERES-Maize crop model and RZWQM water quality model. When this submenu is chosen, the dialog shown in Figure 8 will ask users to select Create Weather Data by WEPP, Convert Weather Data for the Crop Model, or Convert Weather Data for the Environmental Model.

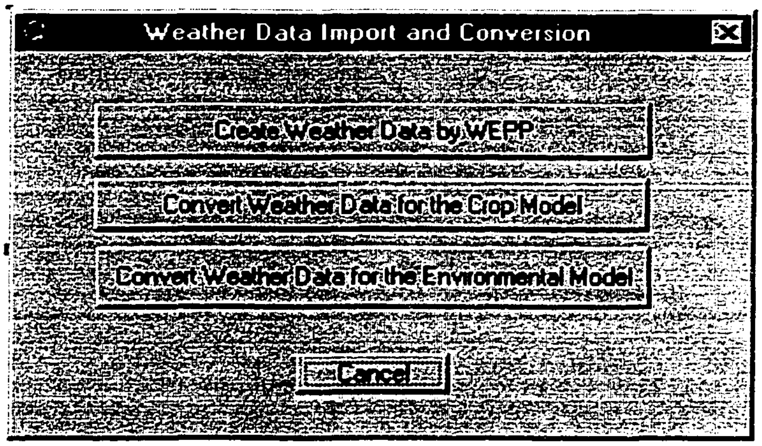


Figure 8 Weather Data Generation and Conversion

6.3.5 Import data from other precision agriculture software packages

SSToolBox and AgLink for Windows are two software packages popularly used for precision agriculture. The submenus of Data menu, Import Coverages of SSToolBox and Import Coverages of AgLink for Windows, may import data created in these two software packages into the IDSSPA. The two submenus use same dialogue shown in Figure 9 to complete the importing processes.

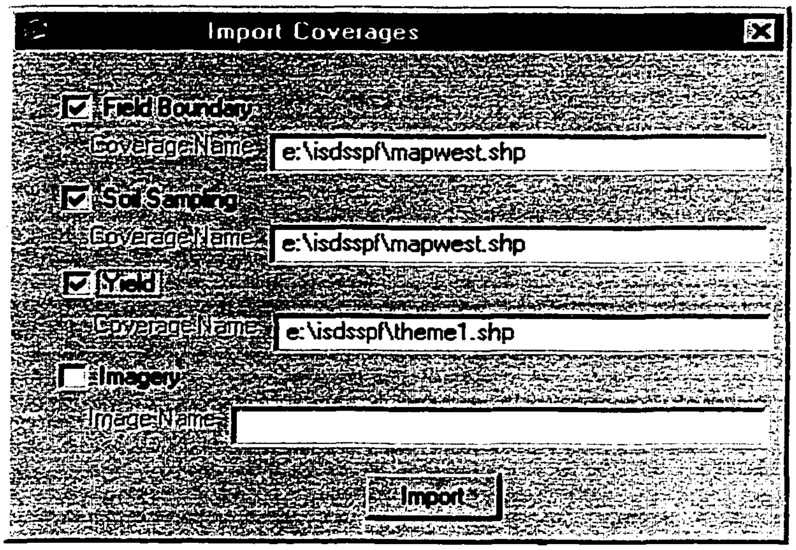


Figure 9 Import Coverages from SSToolBox and AgLink for Windows

6.4 Create Prescription Maps

Using IDSSPA, the user can create lime, P, and K spread maps according to soil sampling data.

6.4.1 Create lime spread map

When select Prescription ⇒ Create Lime Spread Map…, the dialogue shown in Figure 10 asks the user to specify Output Grid Extent, Output Grid Cell Size by inputting Cell Size, Number of Rows, or Number of Cols, and to select interpolator. The following steps are exactly same as manipulating soil texture data shown in Figure 4—7 except that the Z Value Field must be the field storing soil PH value.

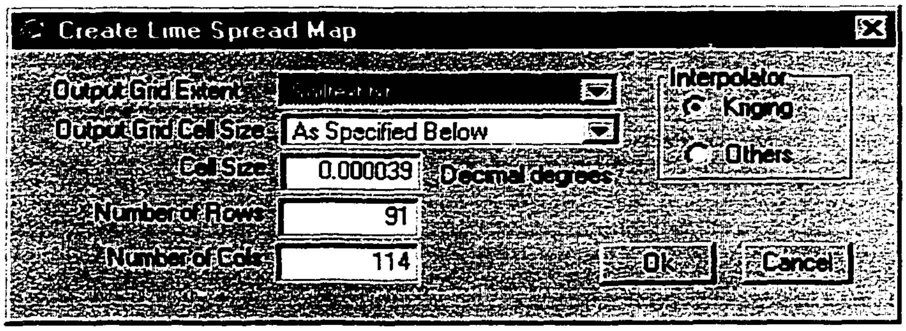


Figure 10 Create Lime Spread Map

6.4.2 Create P spread map

When select Prescription ⇒ Create P Spread Map…, the dialogue shown in Figure 11 asks the user to specify the Yield Goal. The user may continue to create the map by clicking Ok button or stop the process by clicking Cancel button. When Ok button is clicked, another dialogue shown in Figure 12 asks the user to specify Output Grid Extent, Output Grid Cell Size by inputting Cell Size, Number of Rows, or Number of Cols, and to select interpolator. The following steps are exactly same as manipulating soil texture data shown in Figure 4—7 except that the Z Value Field must be the field storing soil P value.

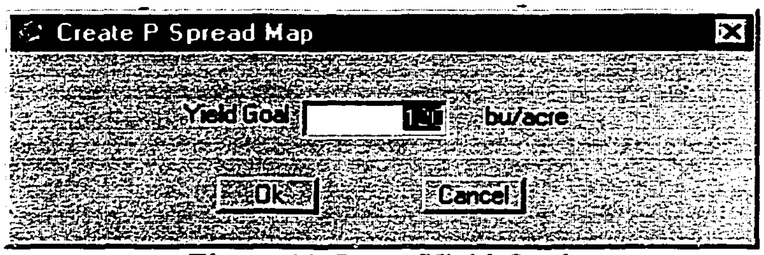


Figure 11 Input Yield Goal

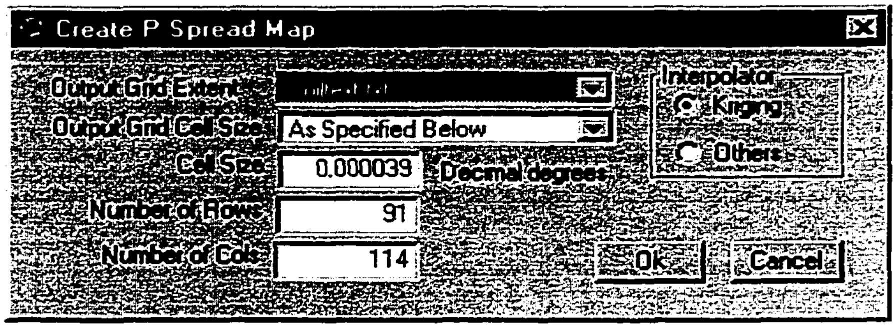


Figure 12 Create P Spread Map

6.4.3 Create K spread map

When select Prescription ⇒ Create K Spread Map..., the dialogue shown in Figure 13 asks the user to specify the Yield Goal. The user may continue to create the map by clicking Ok button or stop the process by clicking Cancel button. When Ok button is clicked, another dialogue shown in Figure 14 asks the user to specify Output Grid Extent, Output Grid Cell Size by inputting Cell Size, Number of Rows, or Number of Cols, and to select interpolator. The following steps are exactly same as manipulating soil texture data shown in Figure 4—7 except that the Z Value Field must be the field storing soil K value.

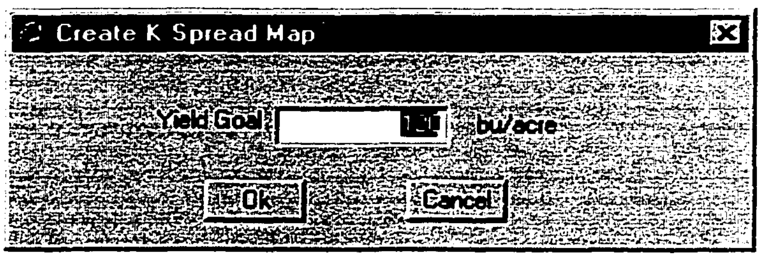


Figure 13 Input Yield Goal

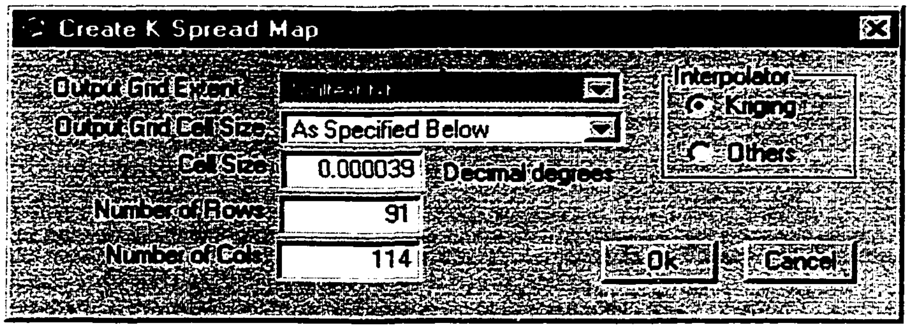


Figure 14 Create K Spread Map

6.4.4 Save the current project as AgView project file

When select Prescription ⇒ Create AgView Project File…, the dialogue shown in Figure 15 comes. The user can select the location to save the project file and specify the file name. Click Ok button, the current ArcView project file will be saved as an AgView project file. Click Cancel button, the conversion process will be stopped.

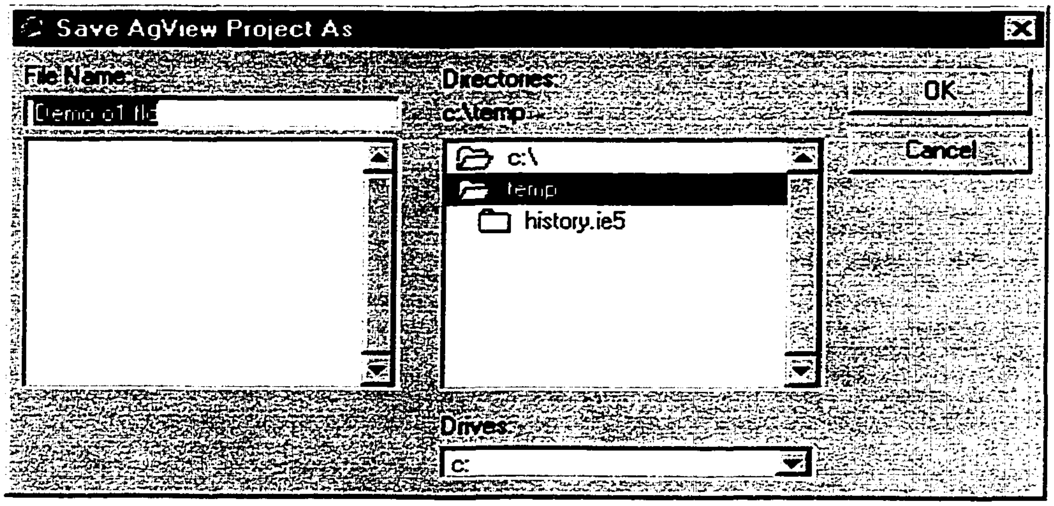


Figure 15 Save the Current Project as an AgView Project File

6.5 Modeling

6.5.1 Crop modeling

When select Modeling ⇒ Crop Modeling, the main dialogue shown in Figure 16 appears. The user may run the crop model by Clicking Run button using the data automatically extracted by the program, or modify the parameters cell-by-cell by clicking the Parameter Input button.

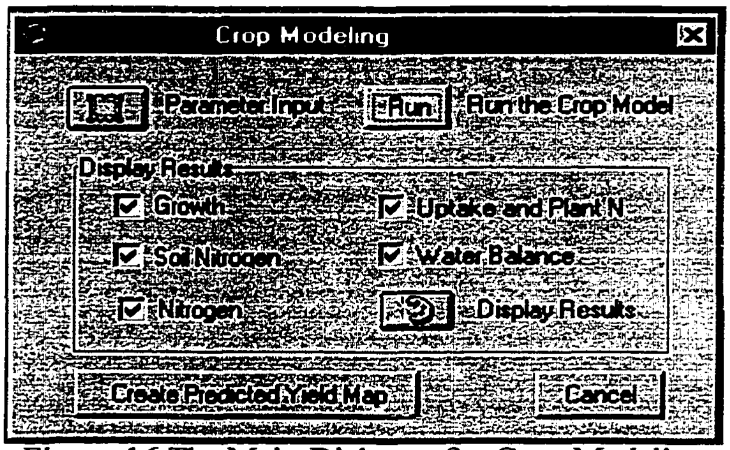


Figure 16 The Main Dialogue for Crop Modeling

When the Parameter Input button is chosen, the user may click any cell to edit its parameters through the dialogue box shown in Figure 17.

The user may specify the output results to be displayed by checking Growth, Soil Nitrogen, Nitrogen, Uptake and Plant N, and Water Balance. The specified results will be displayed cell by cell by selecting the Display Results button and clicking the desired cell (Figure 18). The user can print the results by clicking Print button in Figure 18. Click Cancel button, the system will return to the main dialogue of crop modeling shown in Figure 16.

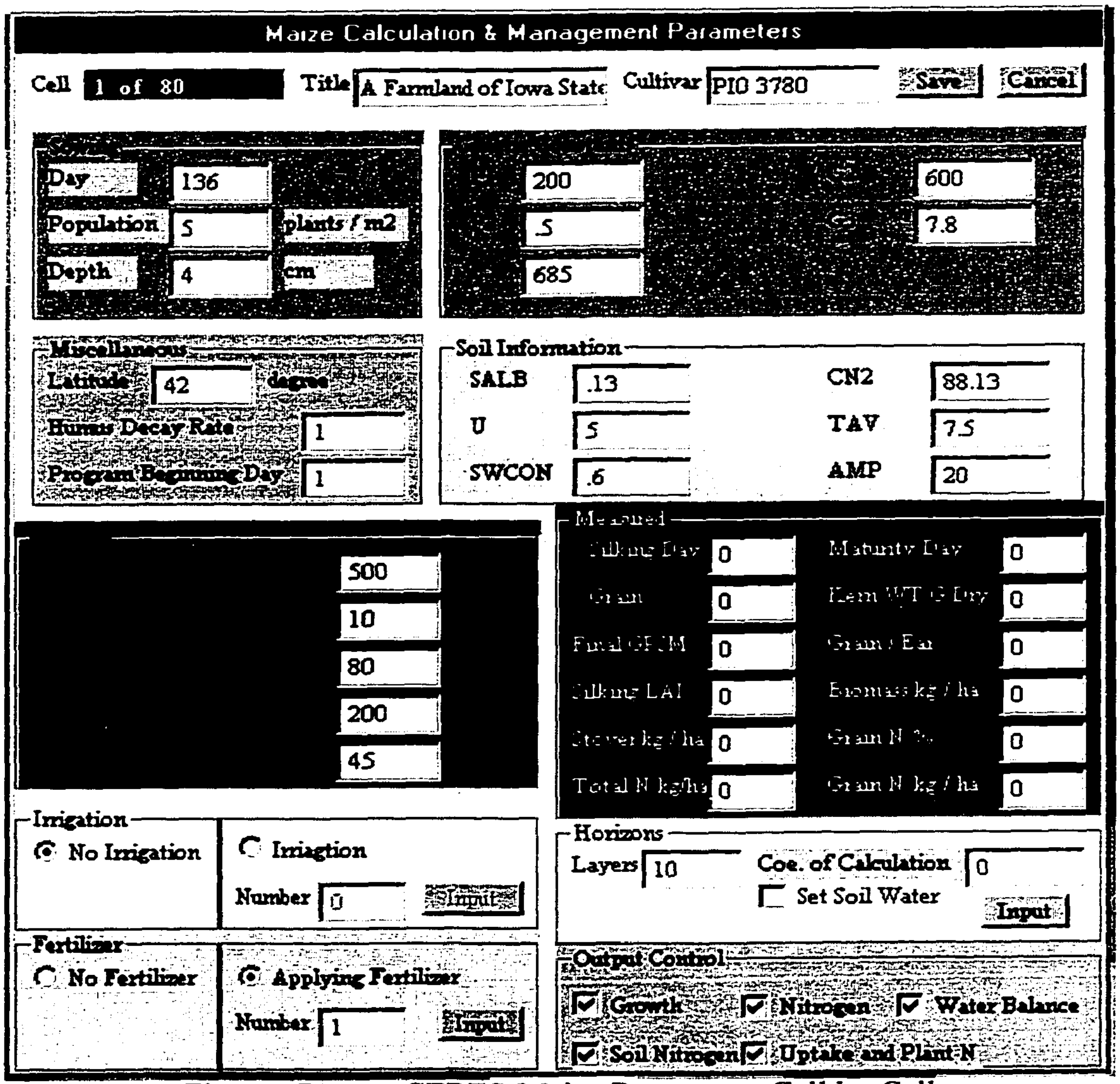


Figure 17 Input CERES-Maize Parameters Cell by Cell

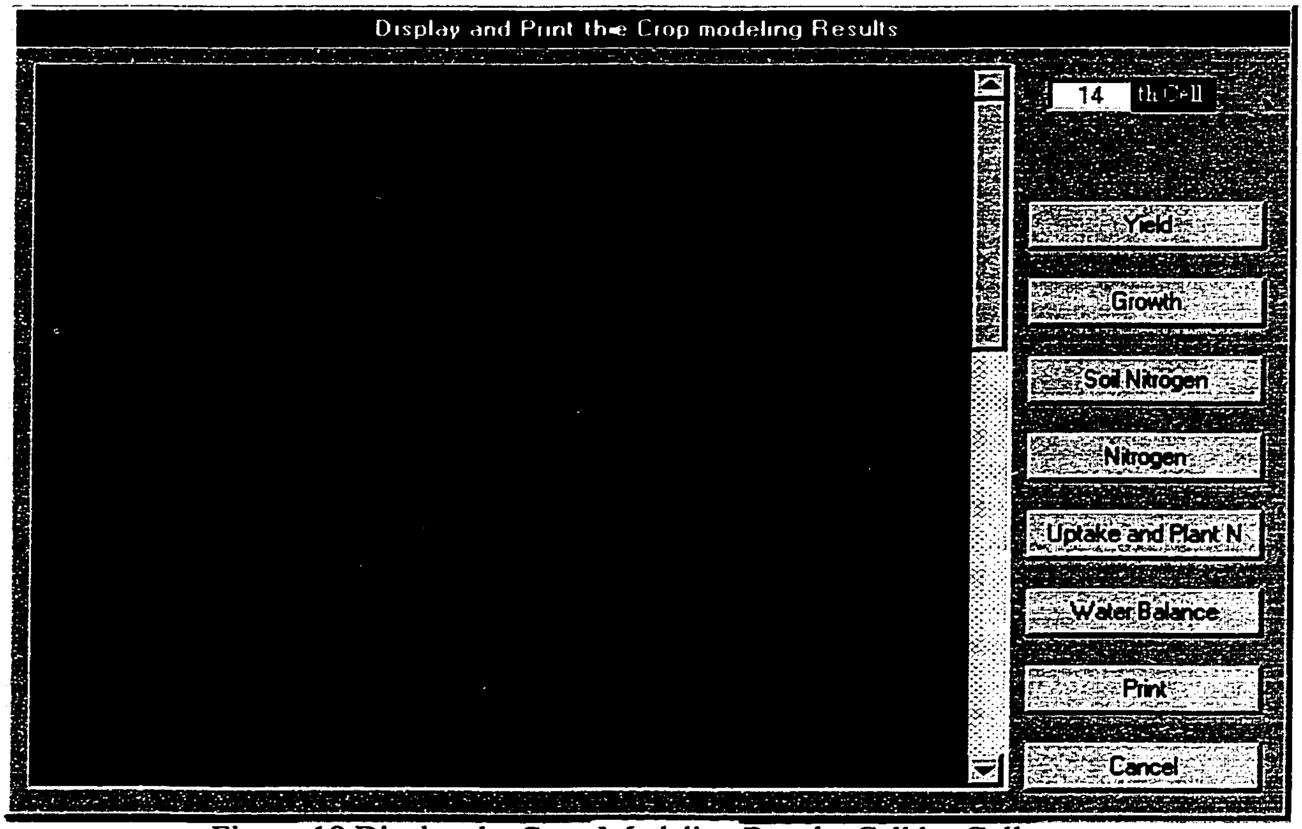


Figure 18 Display the Crop Modeling Results Cell by Cell

6.5.2 Environmental modeling (RZWQM)

When select Modeling ⇒ Environmental Modeling (RZWQM), the main dialogue shown in Figure 19 appears.

Click Initialize Project button to set the working directory where the temporary files will be stored, and select the soil and plot coverages in the dialogue shown in Figure 20. Click Ok button to load and rasterize the soil and plot coverages. Click Cancel button to return to the main dialogue (Figure 19).

Click Prepare RZINIT.DAT button to specify the initial values for the RZWQM model through the dialogue shown in Figure 21.

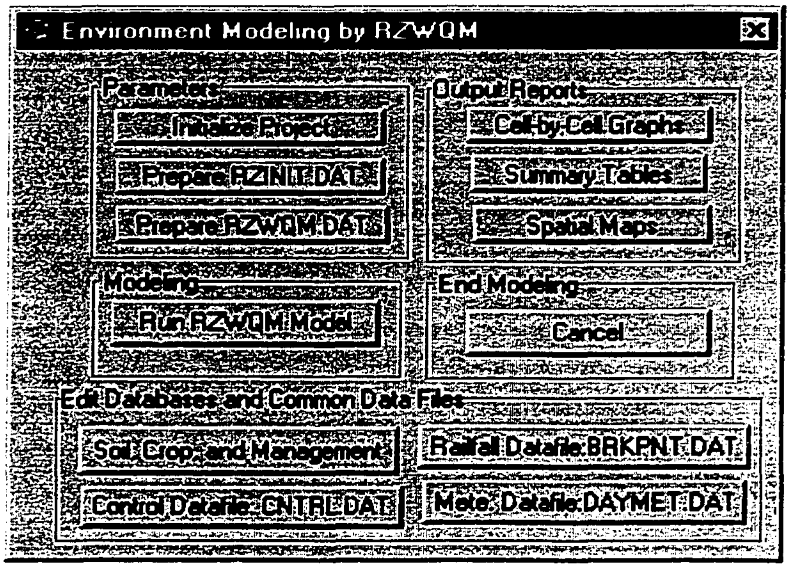


Figure 19 The Main Dialogue of GIS-based RZWQM

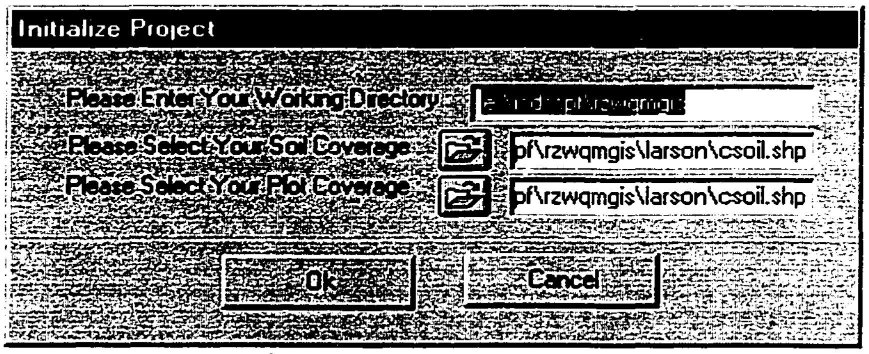


Figure 20 Initialize Project

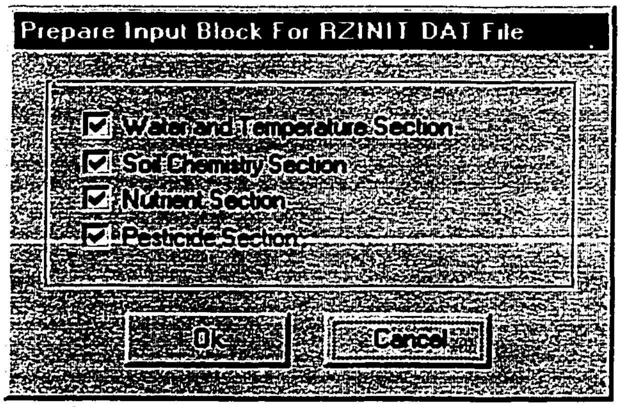


Figure 21 Prepare RZINIT.DAT File

Click Prepare RZWQM.DAT button to input parameters section by section for RZWQ.DAT through the dialogue shown in Figure 22. The Environmental Parameters are inputted through the dialogue shown in Figure 23. Click the button of Soil System Configuration and Properties to complete the soil system physical configuration using the information provided by the Initialize Project. The parameters of macropore and infiltration, potential evaporation, soil chemistry, and management may be inputted and specified through the dialogue boxes shown in Figure 24—27.

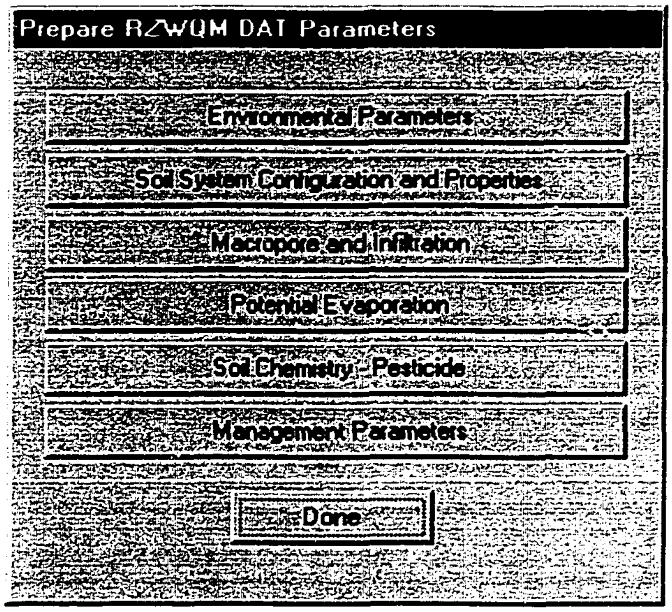


Figure 22 Prepare RZWQM.DAT File

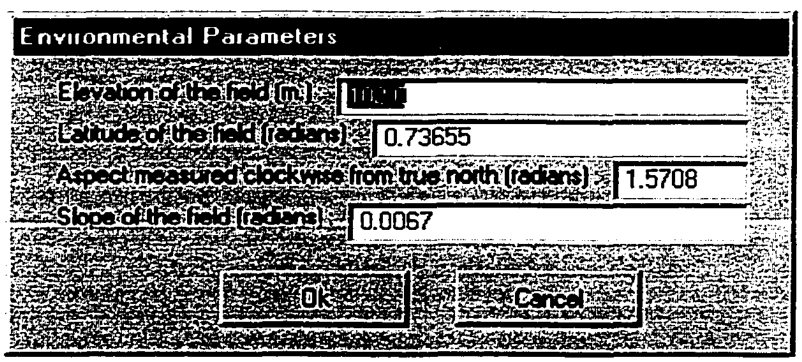


Figure 23 Input Environmental Parameters

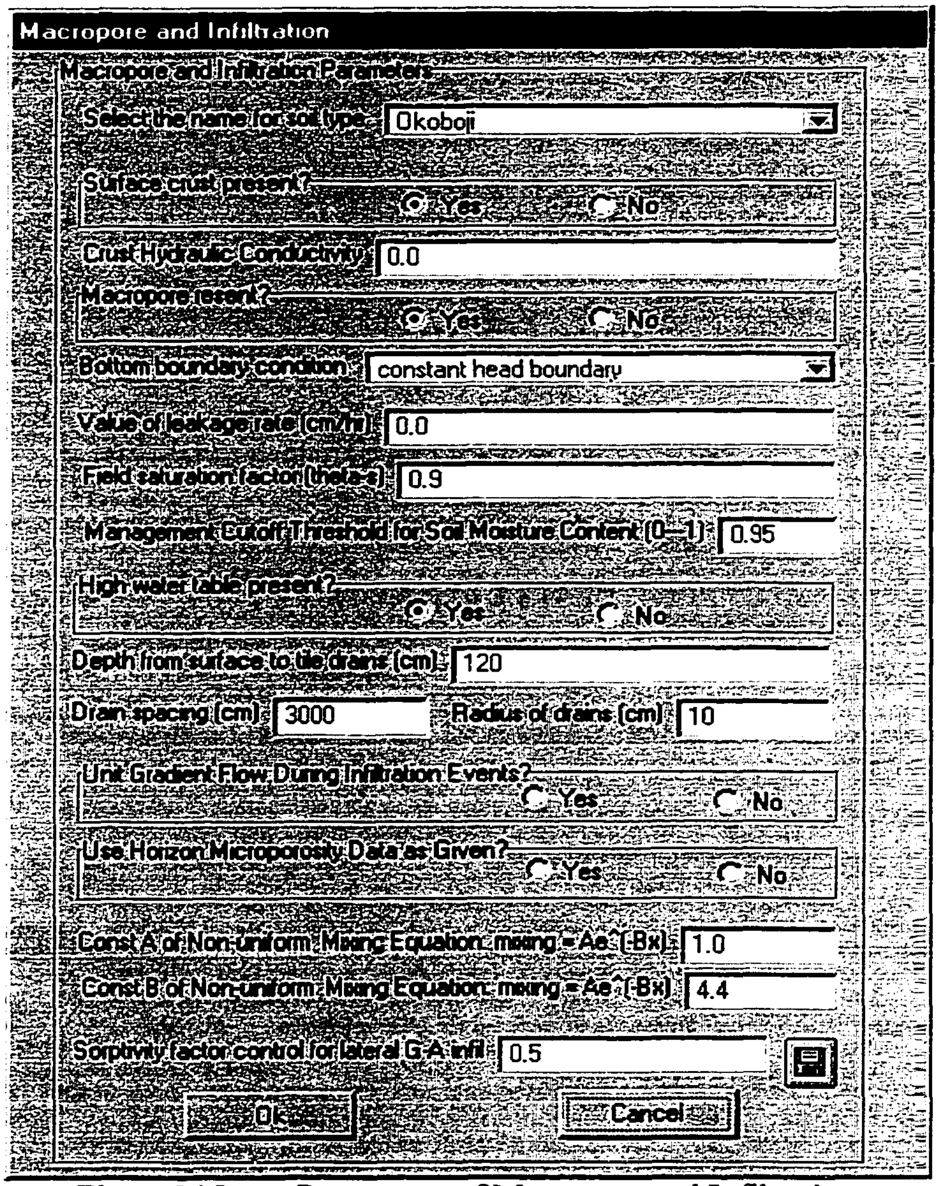


Figure 24 Input Parameters of Macropore and Infiltration

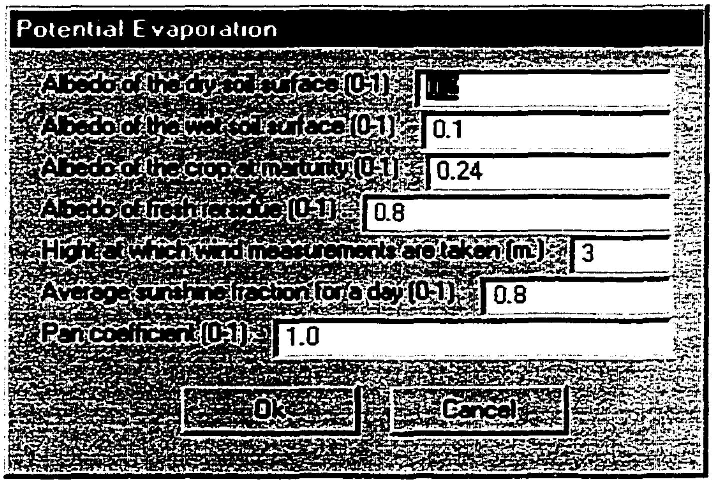


Figure 25 Input Parameters of Potential Evaporation

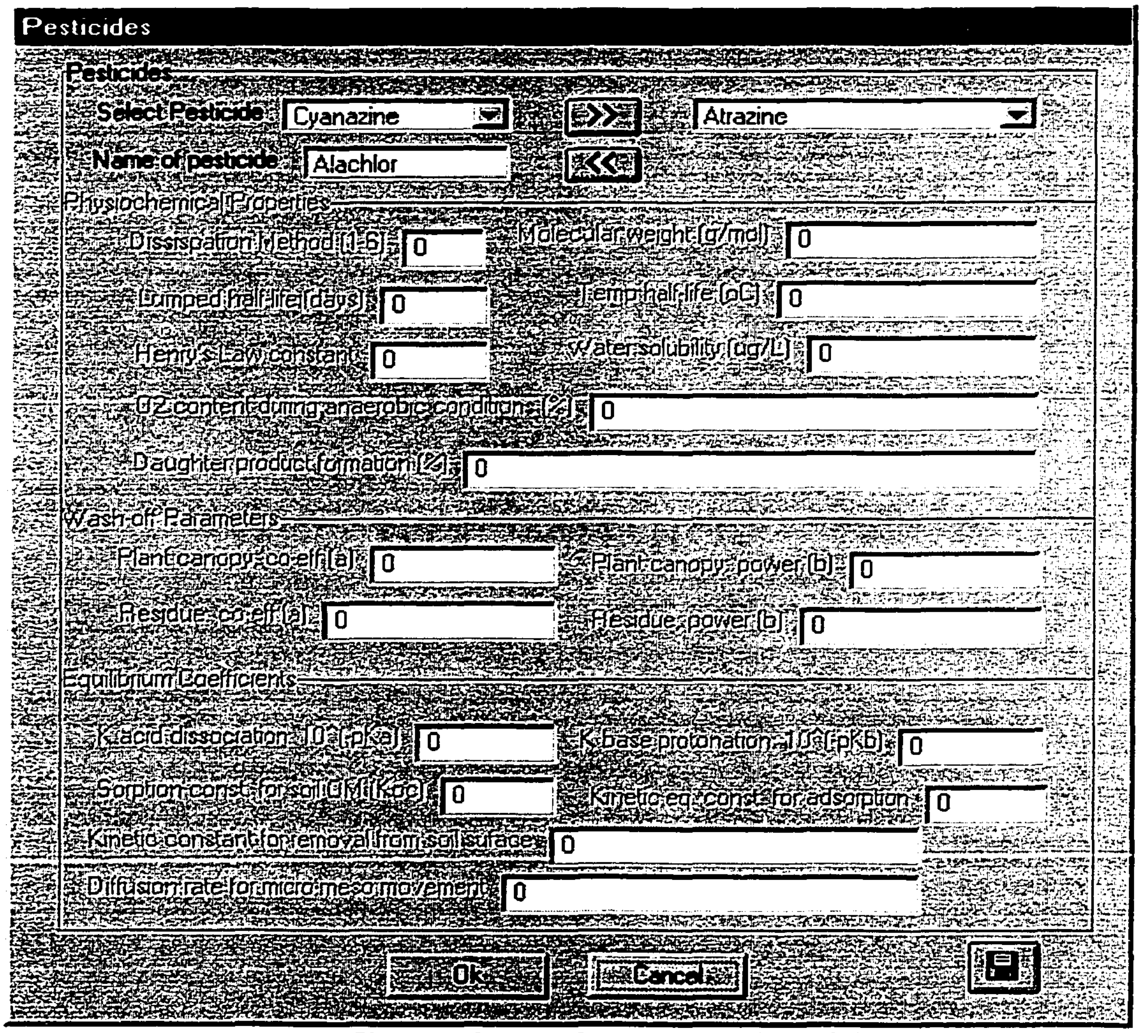


Figure 26 Input Parameters of Pesticides

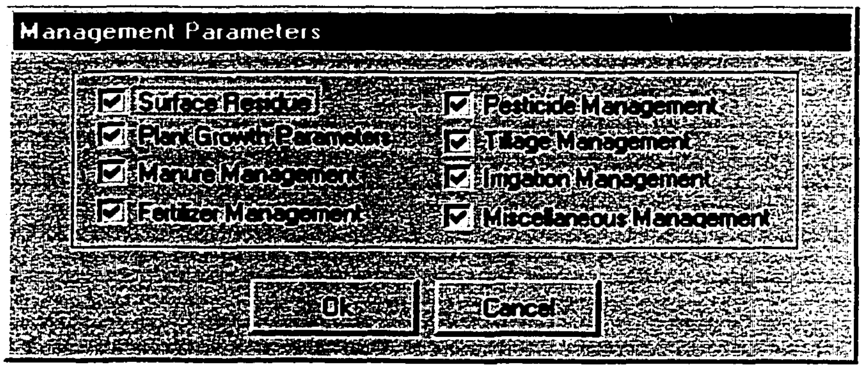
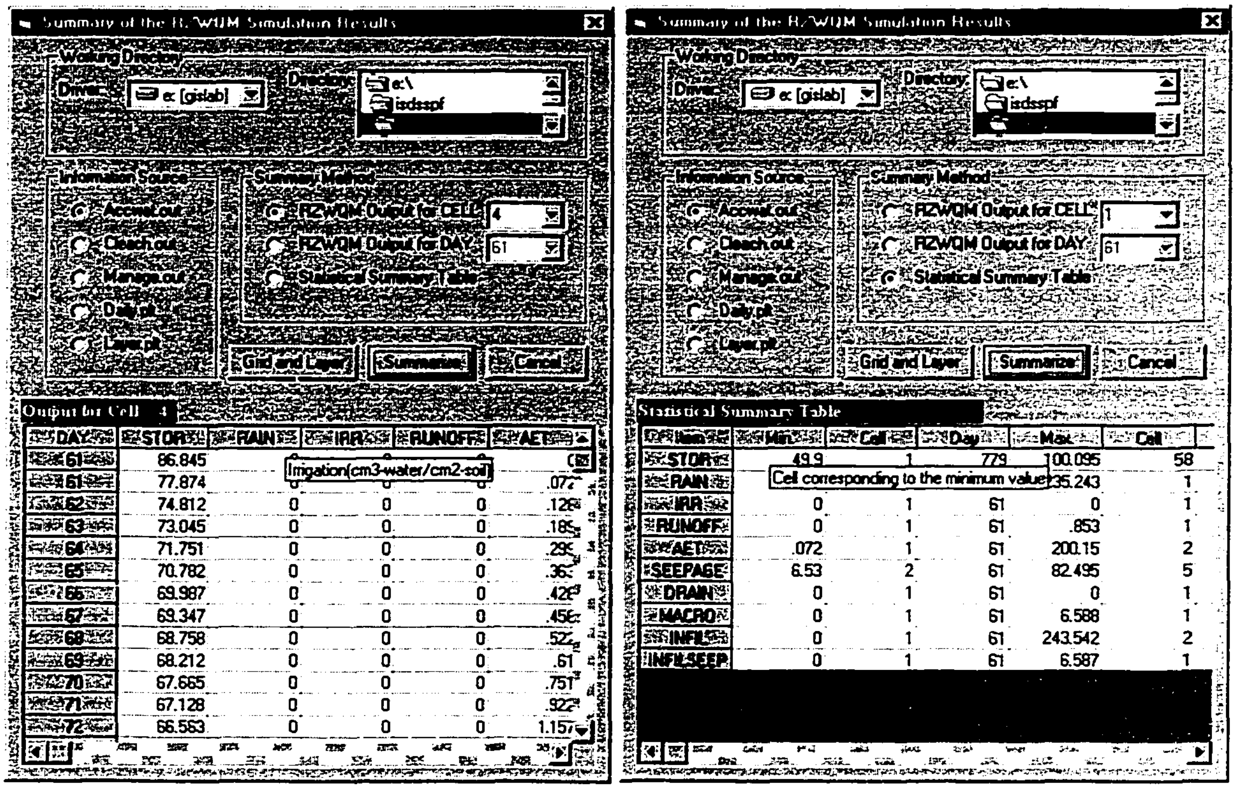


Figure 27 Specify Management Parameters

In Figure 19, click Run RZWQM button to run the model cell by cell. The outputs may be reported as cell-by-cell graph, summary table, and maps. Click the Cell-by-Cell Graphs to display the outputs by curves. Click Summary Table button to display the outputs as various summary tables (Figure 28). Figure 28(a) summarizes the outputs by cell, whereas Figure 28(b) as statistics. In Figure 28, the user can get tip helps by moving the mouse arrow to the table headings and waiting one second. Click Spatial Maps button to display the outputs as maps, including yield map, nitrate-N loss map, and statistical maps showing the minimum, maximum, and average nitrate-N losses.

The databases can be edited by clicking buttons located at the lower part of Figure 19.



(a) (b)

Figure 28 Display the Outputs as Summary Tables

6.5.3 Data Analysis

Using this function, the user can export data to S-Plus for further analyses, or do geospatial analysis.

Click Modeling ⇒ Data Analysis, the dialogue shown in Figure 29 will appear. The user needs to specify the View which includes the themes to be manipulated, and select the theme which includes the data to be analyzed. Click the button of Export Data to S-Plus… to export the data to S-Plus. In order to do geospatial analysis, the user must firstly define the neighbors by clicking the button of Spatial Neighbors…. Then, the user can do the analyses of spatial autocorrelation, local spatial association, and spatial linear regression by clicking the corresponding buttons shown in Figure 29.

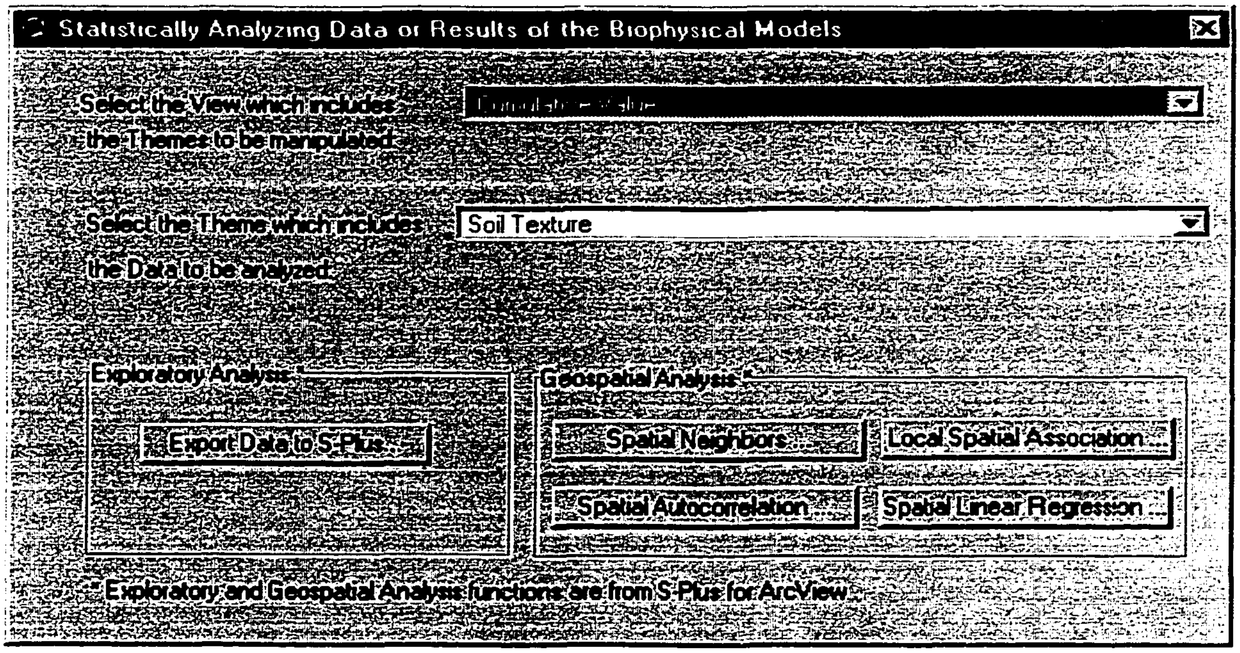


Figure 29 Dialogue for Data Analysis

6.5.4 Benefit/Impact Analysis

Click Modeling ⇒ Benefit/Impact Analysis, the dialogue shown in Figure 30 will appear. The steps to do the analysis are:

- Select the View which includes the needed themes
- Specify the Yield Map, NO3-N Loss Map, N-Fertilizer Map, and Soil Texture Map
- Input the prices and costs the text boxes included in the Current Prices and Capital Costs panel
- Click the button of Do Analysis to create the cost-benefit analysis table in the panel of Cost-Benefit Analysis ($/cell) located at the left-bottom in Figure 30.

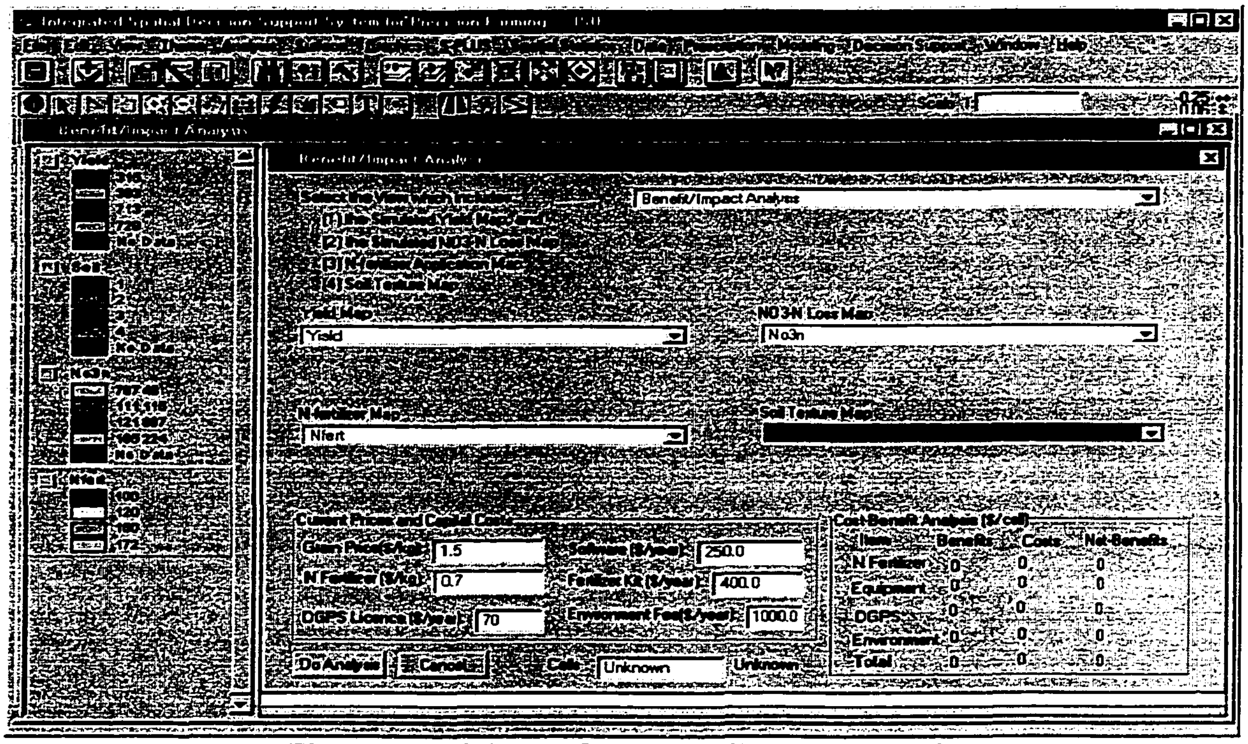


Figure 30 Dialogue for Benefit/Impact Analysis

6.6 Decision Support

In Figure 19, click Decision Support ⇒ Nitrogen Decision Aid, the dialogue shown in Figure 31 appears. The steps to do the analysis are:

- Select the View which includes the needed themes
- Specify the soil map, soil sampling map, and management map
- Specify the weather data file
- Input the start and end dates for analysis
- Click the button of Make Input Files for the Decision Aid to extract and create the input files for the decision aid
- Click the button of Run the Nitrogen Decision Aid to complete the analysis
- Click the button of Create Application Map to show the analysis results as a map

- Click the Cancel button to return to the main interface of the IDSSPA

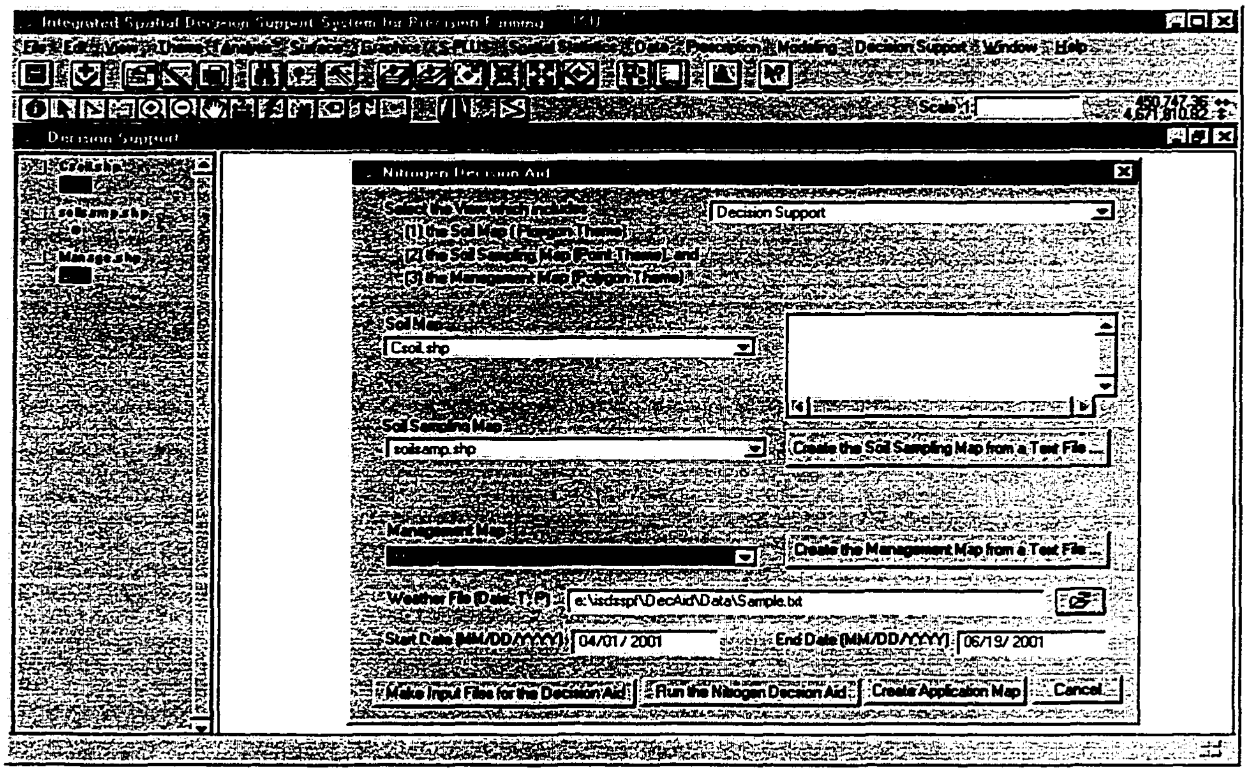


Figure 31 The Dialogue for Nitrogen Decision Aid

CHAPTER 7
CONCLUSIONS

7.1 General Conclusions

1. One of the many goals of precision agriculture is to maximize net farm income and minimize environmental pollution through site-specific variable-rate management of chemicals. Tools are needed to assist resource managers, producers and agribussiness to evaluate potential agronomic, socioeconomic, and water quality implications of precision agriculture. In this study, a decision support system called IDSSPA was developed to include modules for evaluating crop yield and chemical losses in response to site-specific management of agricultural inputs.
2. Using this system, not only can users store, visualize, manipulate, and analyze spatial/non-spatial field experiment data, but they also can do various simulations through the easy-operated biophysical models, which take field spatial variability into account.
3. In the system, the functionalities of the traditional models and analysis methods have been enhanced by coupling them with each other and with ArcView GIS: GIS-based interfaces significantly enhance the ability to make the lumped models be able to consider field spatial variability; statistical and data mining tools are available to analyze field measured data and to further interpret model simulation results; CERES-Maize has been seamlessly plugged into RZWQM as a built-in subroutine to improve RZWQM performances; the tools for evaluating economic and ecologic risks of precision agriculture may be used to do various what-if analyses from the arbitrary

management practice to the practice selected by the GIS-based RZWQM and CERES-Maize models.

4. In this study, four application examples have been designed to demonstrate system functionality and applicability: Example 1 shows how to use GIS-based CERES-Maize; Example 2 shows how to use multivariate statistical techniques and data mining tools to analyze field measured agronomic and environmental data; and Example 3 shows how to use GIS-based RZWQM and to employ statistical models to further interpret model simulation results; Example 4 shows how to use the tools for evaluating economic and ecologic risks of precision agriculture. These examples were reported as separate papers to be submitted for publication in referred journals and organized in chapters in this dissertation.
5. The application examples indicate that IDSSPA can be a useful research and decision make tool for precision agriculture. IDSSPA can be used at different spatial scales (plot, field, landscape, watershed).

7.2 Recommendations for Future Research

A decision support system consisting of data management and exploration, biophysical models, advanced statistical models, and tools for evaluating economic and ecologic risks may be very useful for precision agriculture. The IDSSPA developed in this dissertation has included all of these modules. However, some improvements are needed in the future research:

1. In the current IDSSPA, all of the modules are threaded together through ArcView GIS menus and buttons. All of the scripts are included in one project file and will be loaded

into computer memory while some of them may be unnecessary for the interested analyses. In the future research, the different modules may be as independent ArcView GIS extensions. The users can load one or more these extensions according to their analysis requirements.

2. The data management module may be enhanced. It is a trend that the data providers will distribute their products through Internet. In order to make IDSSPA able to extract the needed data directly from data warehouses, this module may be redeveloped using ArcView spatial database engine (SDE) and ArcExplorer.
3. The venders of the biophysical models are developing Windows versions. These new versions include some effective tools to summarize model simulation results. The future research should consider these tools in the IDSSPA to provide users more alternatives.
4. IDSSPA didn't include the tool to evaluate the benefits of precision agriculture on developing total maximum daily loads (TMDLs). In the author's experience, while some literatures discuss the potential relationship between precision agricultur and TMDLs, there is no such tool. The future research may develop and include such a tool in the IDSSPA.
5. The tool to distribute the outputs of IDSSPA through Internet may be developed using Arc IMS or ArcView IMS. It will convenience users using the results.
6. The decision support component may be extended to include more knowledge. Currently, IDSSPA just provides the nitrogen decision aid. In the future research, decision aids for phosphors, pesticide and tillage may be incorporated in the IDSSPA.

APPENDIX
ACCOMPANYING CD-ROM

System requirements for computer disks: IBM PC or 100% compatibles; Windows 95 or higher; Adobe Acrobat 4.0 or higher.

CD-ROM contains the main interfaces of the IDSSPA and source codes developed in AVENUE and Visual Basic 6.0.

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